EMPIRICAL ANALYSIS OF FARM CREDIT RISK UNDER THE STRUCTURE MODEL

BY

YAN YAN

B.A., Southwestern University of Finance and Economics, 1990
M.A., Southwestern University of Finance and Economics, 1992
M.S., University of Illinois at Urbana-Champaign, 2006

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Doctoral Committee:

Assistant Professor Nicholas D. Paulson, Chair
Professor Peter J. Barry
Professor Gary D. Schnitkey
Professor Hayri Önal
Professor James A. Gentry

ABSTRACT

The study measures farm credit risk by using farm records collected by Farm Business Farm Management (FBFM) during the period 1995-2004. The study addresses the following questions: 1) whether farm's financial position is fully described by the structure model, 2) what are the determinants of farm capital structure under the structure model, 3) how to estimate and test farm asset correlation, 4) what drives farm default, and 5) how to predict farm default and joint default.

In the first part of the empirical study, a seemingly unrelated regression (SUR) model is proposed to investigate the predicting capability of the structure model and test applicability of theories of financial structure to farm business. The model considers dynamic property of the structure model and farm characteristics. A semi-parametric three-stage least squares (3SLS) estimation method is proposed to obtain the estimates and test the model. In the second part, a farm's ability to meet its current and anticipated financial obligations in the next 12 months is predicted by the SUR model connected with credit rating models. In the third part of the study, copula approaches as an alternative are applied to measure farm credit risk under the structure model.

Results indicate that the empirical dynamic model is stable, and the structure model is applicable in explaining most farms' choice of financial structure. In addition, the farms adjust to long-run financial targets for asset-to-debt ratio with additional financing needs following both pecking order and agency theories that is stronger for farms with greater asymmetric information problems.

Application of the SUR model for measuring credit risk indicates that some key financial ratios in credit risk assessment such as liquidity should enter the model; these variables have significant influence on a farm's ability to meet its current and anticipated

financial obligations in the next 12 months. The estimated average asset correlation is 20% while the average default correlation is around 1.2% across farms in the pool. The estimated average asset correlation is clearly higher than the reported average asset correlation of 16% by KMV's risk classing (Lopez 2002). The result indicates that the systematic risk plays a more important role in agricultural production in contrast to other industries.

Estimated average asset correlation from Gaussian and t copula is 11%, similar to that by using a single factor model (Katchova and Barry 2005). The estimated average default correlation from Gaussian copula is less than 1% while it is 3% from t copula. Test results indicate that Gaussian copula is more proper for asset distribution as implied from the FBFM data than t copula.

Results indicate that asset correlation is on average much higher than default correlation, which is consistent with previous findings by Crouchy et al (2002) and Akhavein and Kocagil (2005).

Results indicate that mean asset correlation from multi-factor model is clearly higher than that from Gaussian copula. This is also true for default correlation. Higher asset correlation and default correlation from the multi-factor model lead to relatively higher predicted probability of default and expected loss at portfolio level. Apart from difference in methodology for estimating asset correlation, the relatively lower estimated asset correlation under the copulas approach is more likely due to short time series observations for each involved farm.

Overall, the predicted default rate and expected loss from the multi-factor model at one-year horizon are 0.77% and 0.19% respectively. These values are similar to those reported by FDIC for agricultural loans issued by commercial banks in Illinois for 1995-2004.

Finally, the results illustrate that the methods used in the study can be also applied to agricultural lending using available farm records, which provides a solution to the two major issues in risk assessment for agricultural lending, i.e. lack of long-time loss data and limited information of macroeconomic factors on changes of farm assets.

To Rebecca and Xiangdong Shi

To my Mom and Dad

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CHAPTER 1

INTRODUCTION

In a value-at-risk (VaR) framework, expected loss and unexpected loss at portfolio level are determined by probability of default (PD), loss given default (LGD), exposure at default (EAD), and default correlation (Barry 2001 and 2004, Saunders and Allen 1999, Caouette et al 1998). When Merton's structure model (1974) is applied in credit risk measurement, default probability is often measured as the probability of an agent's asset value falling below a threshold point, say total debt (Crouhy and Galai 1986, Crouhy et al. 2000, Gordy and Heitfield 2001). Default correlation is then determined by each agent's probability of default and joint default for any two agents when a default event follows Bernoulli distribution. Since marginal probability of default and default correlation are in practice closely associated with asset correlation, credit risk measurement under the approach generally relies on both the structure model and joint normal assumption of asset returns (Grouhy et al 2000).

The structural model can address a firm's choice of financial position. In this sense, the choice is determined by asset return and its volatility. Whether there exists such specific association between response and predictor remains to be checked empirically. Proponents of the model state that the structure model "provides a rigorous, internally consistent framework from which we can draw economically meaningful inferences. Because the parameters that characterize structural models have economic interpretations, they lend themselves to scrutiny on theoretical as well as empirical grounds." And compared to multivariate factor models, "models with fewer parameters are generally more easily identified by available data, and parameters can be estimated more efficiently. Highly parameterized models have a tendency to "over-fit" observed data, reducing the effectiveness of out-of-sample forecasts" (Gordy and Heitfield 2001, pp.16-17). While theoretically elegant, there is some controversy over its empirical application. For example, in the case of measuring credit risk, the model tends to "produce probabilities that are unrealistic in practice" (Stein 2000, pp. 3). A recent study using KMV[1]model to farm records illustrated large difference between the predicted default rate and the actual one from the data (Katchova and Barry 2005). Therefore, modeling of joint default and prediction accuracy as compared to historical default rates captures more and more concerns (Altman 2000 and 2002, Barry 2004, Stein 2000, Gordy and Heitfield 2001, Frey and McNeil 2003, Crouhy et al 2000, Bouyé et al 2000, Boyer et al 1999, and more). Ericsson et al (2005) found that the under-prediction seems mainly due to factors not included in the structure models rather than the prediction capability, while Caouette et al (1998, pp.148) pointed out "by narrowing down the range of possible variables and types of interactions… there is possibility of under-fitting (excluding what may be an important variable)". In this sense, an empirical model based on the structure model should be a better choice for proper fitting.

On the other hand, asset correlation is often calibrated by factor models that relate change in asset values to changes in a small number of economic factors (Gordy 2003, Koyluoglu and Hickman1998). The main reason is "to reduce dramatically the number of asset correlations to be calculated" (Crouhy et al 2000, pp. 103). Akhavein and Kocagil (2005) showed that average five-year intra-industry asset correlation for US issuers is 24.09% for 1970-2004 with a multi-factor model[2]. In agricultural lending, the reported average assets correlation is around 10.05% by applying a single factor model to farm reported asset returns for 1995-2001 (Katchova and Barry 2005). Although default correlation, marginal probability of default and asset correlation are closely related, the connection was not directly

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[1] KMV is a trademark of KMV Corporation. Stephen Kealhofer, John McQuown and Oldrich Vasicek founded KMV Corporation in 1989.

[2] The issuers are classified into one of Fitch Ratings' 25 industry categorizations, and the value of 24.09% is the average correlation across the 25 industries.

emphasized in these studies that mainly focus on common economic factors for an industry, region and/or country.

Most popular credit risk models based on the structure model in commercial lending, such as KMV's expected default frequency model (EDF), pre-require information on macroeconomic factors and long-time loss data for computing asset correlation and default rate. However, the prerequisites are hard to meet with farm records on which majority of the lending decisions are based. In this sense, if only farm records are available for measuring credit risk, it is impossible to directly use these models to assess asset correlation and then default risk.

To address these problems, the paper proposes a Merton model (1974) based seemingly unrelated regression model (SUR) to investigate capability of the structure model in prediction and test applicability of theories of capital structure to farm business. The work considers the dynamic property of the structure model and farm characteristics. The SUR model is then used to predict a farm's ability to meet its current and anticipated financial obligations in the next 12 months by connecting to credit scoring models. For comparison, copulas approach is introduced as an alternative in measuring asset correlation and predicting default. Given the models, asset correlation is estimated firstly and then farm credit risk is predicted by simulation. Before that, default definition is investigated and default thresholds are inferred from farm records.

The dissertation is organized as follows. Chapter 2 reviews credit risk measurement under the structure model and theories of capital structure. Chapter 3 introduces definition of default and the data. Chapters 4, 5 and 6 covers empirical studies on capital structure under the structure model, estimation of asset correlation and robust test, prediction of farm default and joint default. Chapter 7 gives and compares the predicted expected loss and unexpected loss at portfolio level. Chapter 8 concludes.

CHAPTER 2

MERTON MODEL BASED CREDIT RISK MEASUREMENT: LITERATURE REVIEW

This chapter reviews Merton's structure model (1974) that addresses a firm's financial position. The model of financial position under the structure model is stochastic dynamic assuming that debt is exogenous. In contrast, theories of capital structure pay attention to debt level and its association with financial position.

2.1 Merton's Model and Financial Position

Under the framework of Merton's model, the value of farm i 's asset A_{it} at time t is assumed to follow a standard geometric Brownian motion

1) $$A_{it} = A_{i0} \exp((\mu_i - \frac{\sigma_i^2}{2})t + \sigma_i \sqrt{t}\omega_{it}))$$

where A_{i0} is the initial asset value, μ_i is the instantaneous expected rate of return, σ_i is the standard deviation of the return on the underlying asset, and ω_{it} is of $N(0,1)$ that equal to

2) $$\omega_{it} = \frac{\ln(A_{it}/A_{i0}) - (\mu_i - \frac{\sigma_i^2}{2})t}{\sigma_i \sqrt{t}}$$

In practice, the model provides a convenient way to illustrate the farm's financial position. By proper transformation, the structure model can be written as

3) $$\ln A_{it} = \ln A_{it-1} + (\mu_i - \frac{\sigma_i^2}{2}) + \sigma_i (\sqrt{t}\omega_{it} - \sqrt{t-1}\omega_{it-1})$$

Let $\varepsilon_{it} = \sigma_i (\sqrt{t}\omega_{it} - \sqrt{t-1}\omega_{it-1})$, then we have ε_{it}~N (0, (2t-1) σ_i^2) assuming $E(\omega_{it}\omega_{it-1}) = 0$.

When t=1, we have $\varepsilon_{it} \sim N(0, \sigma_i^2)$. Subtracting $\ln D_{it}$ from both sides of equation (3) yields

4) $$\ln\frac{A_{it}}{D_{it}} = \ln\frac{A_{it-1}}{D_{it}} + (\mu_i - \frac{\sigma_i^{\ 2}}{2}) + \varepsilon_{it}$$

where D_{it} denotes debt value at the time. This is a stochastic dynamic model of financial position that is determined by the lagged value of log of asset-to-debt ratio, expected asset return and its volatility. It is noted that debt is exogenous under the model, which is contrast to capital structure theories that pay more attention to debt level and its association with financial position.

2.2 Theories of Capital Structure and Farm Characteristics

In corporate finance, one of the most important decisions confronting a firm is the design of its capital structure that is often illustrated by its asset-to-debt ratio. Actually, determinants of a firm's capital structures have long been an important area ever since Miller and Modigliani's pioneer work in 1958. There are several important theories in the field including trade-offer theory, pecking order theory, agency theory, and signaling theory.

Of a firm's choice of capital structure, the trade-off theory is the oldest, which indicates that a firm optimizes its debt level such that marginal tax advantage of additional borrowing is offset by the increase in the cost of financial distress and bankruptcy. According to Myers (1984), firms adopting this theory could be regarded as setting a target asset-to-debt ratio with a gradual attempt to achieve it. Under the theory, issuing equity means moving away from the optimal financial position and thus should be considered as bad news.

The followed pecking order theory says that firms prefer to finance their investments from internally generated cash flow as their first best choice in contrast to borrowing (Myers and Majluf 1984). In view of this theory, internal funds incur no flotation costs and require no disclosure of a firm's proprietary financial information that may include the firm's potential investment opportunities and gains that are expected to accrue as a result of undertaking such investments. In this sense, there is an obvious cost saving advantage from internal financing, and external financing is only applicable when there is an imbalance between internal funds and real investment opportunities.

The agency cost theory states that an optimal capital structure is determined by minimizing the costs arising from conflicts between the parties involved (Jensen 1986). For example, the potential conflict of interests between the borrower and the lender may lead to either divert the funds to intended uses or finance risky activities by the borrower that adversely affect the likelihood of loan repayment. The lender may thus require a higher return for their funds if there is potential for this transfer of usage.

Signaling theory proposed by Ross (1997) is also based on asymmetric information. Under the theory, investors interpret higher level of debt as a signal of higher credit quality and higher future cash flows. Due to the high-expected costs of financial distress at any debt level, lower credit firms cannot mimic higher credit firms by taking on more debt.

These theories imply that the optimal capital structure depending upon farm characteristics differs across farms. The particular farm characteristics, including farm size, growth opportunities, profitability, collateral position, non-debt tax shield, and tenure, are closely related to farm capital structure.

Farm Size: Farm size is represented by log of farm cash sale (Size). In light of pecking order, signaling and agency theories, since farm business is typically small in size and has limited access to equity market due to asymmetric information, farms would tend to be more relied on debt financing as their sale increases.

Growth Opportunities: A farm's growth opportunities are considered as an important determinant of its capital structure. Annual growth in total assets (GTA) was used as a measure of growth opportunities in previous empirical studies in the sense that "the growth in assets is a direct measure of current investment and, if investment is persistent, it is also a proxy for expected investment" (Fama and French 2002, pp. 8). In the study, the normalized annual growth in total assets (NGTA), normalized by its volatility, is proposed to represent a farm's growth opportunities. Because internal financing is not likely to fill the needs of growing farms, the pecking order theory would predict that these farms are likely to hold more debt. However, due to the increase cost of bankruptcy and asymmetric information, the other three theories suggest the opposite.

Profitability: Farm profitability or potential cash flow is described by log of farm cash sale to total debt ratio (Profit). In light of pecking order theory that farms prefer financing through retained earnings first before moving to debt, farms with high profitability and hence high opportunities to retain earning should have lower debt. Moreover, as strong cash flow may serve as an alternative signal of quality, there is no need for these farms to distinguish themselves from lower quality farms by taking on more debt. In contrast, trade-off theory suggests that high profitability farms are less likely to go bankrupt, and thus can sustain more debt, while agency theory predicts that the need to refrain the borrower from taking riskier actions would lead to a negative relationship between profitability and debt level.

Collateral Position: Collateral position is measured by value of farmland plus machinery and equipment to total assets (Collateral Ratio). Since selling secured debt is beneficial to a firm because issuing secured debt can avoid the costs of issuing securities, firms with more collateral value in their assets tend to issue more debt to take the advantage of the low cost, as stated in Myers and Majluf (1984). Similarly, the trade off theory also predicts such positive relationship as farms with a relatively large portion of tangible asset would also have higher liquidation values, which in turn reduce the bankruptcy costs. On the other hand, Grossman and Hart (1982) pointed out that the agency problem between the lender and the borrower would suggest the opposite relationship between debt and the collateral value of assets. Since farmers usually have limited access to security market, the pecking order theory may not be applicable to explain the relationship between farm financial position and collateral ratio.

Non-debt Tax Shield: The paper follows Titman and Wessels (1988) and uses the ratio of depreciation over total assets to represent a farm's non-debt tax shield (Shield). Since tax deductions for depreciation and investment tax credits are substitutes for the tax benefits of debt financing, farms with large non-debt tax shield would tend to include less debt in their capital structures as predicted by the trade off theory.

Tenure: Tenure is measued by owned land to total tillable land ratio. According to trade off theory, farmers tend to reduce their debt level with increasing owned land. On the other hand, it is well known that crop production, in contrast to other industries, is often characterized by annual and seasonal production cycles as well as life cycle patterns and that these characteristics have important financial implications and thus impact on farm financial position (Barry 2004). For example, compared to older farmers, younger farmers tend to rely more heavily on leasing farmland and operate on a relatively small farm.

Previous empirical studies on capital structure mainly support both pecking order theory and trade-off theory (Titman and Wessels 1988, Barry et al 2000, Fama and French 2002, Myers and Majluf 1984, Schoubben and Hulle 2004, Zhao et al 2008, and more). Titman and Wessels (1988) showed that debt levels are negatively related to the uniqueness of a firm's line of business and there is a transaction cost induced pecking order for investment funds. Barry et al (2002) found that older farmers adjust to their long-term debt target quicker than younger farmers while the latter adhere more closely to the leasing/long-term debt pecking order. Schoubben and Hulle (2004) suggest that determinants of capital structure differ between quoted and non-quoted firms. For the capital structure of private firms, growth opportunities and the proportion of current assets seems to play more important roles.

2.3 Financial Position and Credit Risk

Generally default occurs once asset value falls below debt level (Crouhy and Galai 1986). Under the structure model, probability of default is used for measuring credit risk. For a known debt value D_{it} at time t, the probability of asset value falling below this debt value is then given by

$$5)\qquad \mathrm{P}(\mathrm{A}_{\mathrm{it}} \leq \mathrm{D}_{\mathrm{it}}) = P\left(\omega_{it} \leq -\frac{\ln(A_{io}/D_{it}) + (\mu_i - \frac{\sigma_i^{\,2}}{2})t}{\sigma_i \sqrt{t}} \right) = \Phi(z_{it})$$

where $z_{it} = -\dfrac{\ln(A_{io}/D_{it}) + (\mu_i - \frac{\sigma_i^{\,2}}{2})t}{\sigma_i \sqrt{t}}$, $\Phi(\cdot)$ is the standard normal cumulative distribution function. Figure1 shows the distribution of the asset value A_{it} assuming positive expected asset growth over time and debt value D_{it} at time t for the farm, and the probability of asset value falling below this debt value, $\mathrm{P}(\mathrm{A}_{\mathrm{it}} \leq \mathrm{D}_{\mathrm{it}})$, which is the area below D_{it}.

It is noted that the calculated probability is not necessarily equivalent to probability of default. One issue is whether debt level is exogenous in this model. If not, the factors implied in the capital structure theories mentioned above need to be considered under the model. Another issue is the content of debt, accounting value or market value, intermediate and long-term liabilities, current liability or total liabilities. Clarification of debt component is closely linked with a clear definition of default.

More important is that the asset-to-debt ratio (A_{it} / D_{it}) in the equation actually illustrates a farm's solvency level instead of default. Under the circumstance, low asset-to-debt ratios are often interpreted as an indicator of "farm financial stress". For example, in 1988, the U.S. Department of Agriculture (USDA) indicated that farms with debt-to-asset ratio above 0.7 ($A_{it} / D_{it} < 1.43$) were likely to experience a very high level of financial stress, and may have to liquidate certain assets in order to improve their financial position. In this sense, the probability predicts the likelihood of severe financial stress at time t instead of default probability. For accurate prediction of default, an adjustment is often needed (Crouhy et al 2000, Altman 2002). For example, the reported default probability for an issuer by KMV is obtained by "mapping the DD (distance-to-default that is equal to the normalized asset value of z_{it} in expression (5)) to the actual probabilities of default for a given time horizon" (Crouhy et al 2000, pp. 90). The actual probabilities of default, called default thresholds or historic default rates, are inferred from KMV's default database while the mapped probability is called expected default frequency (EDF).

2.4 Credit Risk Measurement under the Structure Model

Under mean-variance method, measurement of credit risk at portfolio level requires prediction of default rates and joint default rates by simulation based on asset correlation, where asset correlation is estimated by multi-factor regression model with known information on macroeconomic factors as independent variables. The correlation among the farms may be zero, but more frequently it is not equal to zero due to, for example, geographic connection in farm production, implying that we need to pay attention to its estimation.

Default correlation is generally inferred from the predicted default rates and joint default rates. Assuming that a default event follows Bernoulli distribution, default correlation τ_{ij} for any two farms i and j is given by

6)
$$\tau_{ij} = \frac{P_{ij} - P_i P_j}{\sqrt{P_i(1-P_i)P_j(1-P_j)}}$$

In the equation, $P(\cdot)$ denotes the predicted marginal probability of default for each farm and P_{ij} refers to the predicted joint probability of default for farm i and farm j. The standard deviation (std.) of farm i's default and the joint probability of default P_{ij} are given by

7)
$$\begin{aligned} Std(\text{farm i in default}) &= \sqrt{P_i(1-P_i)} \\ P_{ij} &= P_i P_{j/i} \end{aligned}$$

where $P_{j/i}$ denotes the conditional probability of default for farm j given that farm i is in default. The conditional probability is easy to calculate by using simulation.

Given the probability of default (PD), loss-given-default(LGD), and default correlation matrix, the credit risk at portfolio level is then measured by the expected loss (EL) and unexpected loss (UL). They are given by

8)
$$\begin{aligned} EL &= \sum_{i=1}^{n} w_i P_i LGD_i \\ UL &= \sqrt{\sum_{i=1}^{n} w_i^2 UL_i^2 + \sum_{i=1}^{n}\sum_{j>i}^{n} w_i w_j \tau_{ij} UL_i UL_j} \end{aligned}$$

where $UL_i = LGD_i \sqrt{P_i(1-P_i)}$, and w_i is the weight for farm i and n is the total number of farms in the portfolio. The expected loss is often regarded as an anticipated cost of doing business while the unexpected loss represents the volatility or standard deviation of the loss.

CHAPTER 3

DATA AND FARM DEFAULT

The empirical analysis of the study uses Farm Business Farm Management (FBFM) data for 1995-2004. The data do not include macroeconomic factors and long time loss information. To address the issue, definition of default is investigated and used to find out historical default rates from the farm records. A description of the data and the treatment of missing values for the following analysis are also illustrated in this chapter.

3.1 Definition of Default and Its Implication

As mentioned in the introduction, one of the difficulties in measuring farm credit risk is lack of long time loss data. Due to the difficulty, this study uses two alternative sources of historical default rate. One is FCS (Farm Credit System) default guideline that will be introduced in the following part. The other is from investigating farm records by reconsidering definition of default.

In a study on bank capital requirement by Crouhy and Galai (1986), they suggested that default occurs once asset value falls below debt level. However, the scenario may not imply real default. Altman (1968, pp. 591) once pointed out that, for a firm with poor solvency, “because of its above average liquidity, the situation may not be considered serious”, i.e. the firm could actually be in the state of financial stress instead of default. Some studies on default, using the structure model under the definition, illustrated large differences between the predicted default rates and the reported values (Stein 2000, Crouhy et al 2000, Katchova and Barry 2005).

The Basel II[3] (2004, pp. 92) also suggested a conservative definition on default for a bank, “a default is considered to have occurred with regard to a particular obligor when either or both of the two following events have taken place,

- The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held).
- The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstanding.”

The second event is close to the industry accepted standard that 90 days delinquency and assignment to non-accrual loans (Barry et al 2004, Stam et al 2003). However, since the FBFM data do not cover the real loss information related to the standard, we pay more attention to the first scenario, i.e. unlikelihood of paying back on debt held by an obligor.

It is known that the farm financial crisis in 1980s is associated with rapid deterioration of farm return on asset and severe debt problems as measured by debt-to-asset ratio and interest rate. In corporate finance, on the other hand, if an issuer belongs to the speculative grade under Moody’s risk rating matrix, the firm will be also assigned a speculative-grade liquidity rating (SGL) as an assessment of its ability to cover its cash obligations by its projected cash flow over the coming 12 months. The ratings mainly assess an issuer’s operating income, current and anticipated cash balance, and internal and external sources of liquidity. Puchalla and Marshella (2007, pp. 1) showed that weak SGL is highly correlated with high probability of default, and “every company that has defaulted in roughly

[3] Basel II is the second of the Basel Accords, which are recommendations on banking laws and regulations issued by the Basel Committee on Banking Supervision. The purpose of Basel II is to create an international standard that requires financial institutions to maintain enough capital to cover risks incurred by operations.

the last five years through a bankruptcy or missed payment was rated SGL-4 (weak SGL) at the time of default". By incorporating with these findings and considering that only farm records are available in the study, a farm is defined as defaulted if it can not meet its current and anticipated cash balance over the coming 12 month (expected obligation) in combination with poor position in liquidity and return on asset (ROA) as well as heavy burden on interest payment relative to its operating income. Specifically, a farm is in default for any given year if all of the following conditions are satisfied,

- Ratio of farm reported market value of asset over the expected obligation in the near future is less than 1;
- ROA is less than 0;
- Ratio of current debt to current asset is higher than 1.25;
- Ratio of farm reported interest expense and accrued interests over value of farm production is higher than 10%.

When farm records indicate the current portion of intermediate and long-term liabilities (TLD) as well as the total balances of these categories of liabilities, a farm's current liability plus one half of intermediate and long-term liabilities can be treated as a proper proxy for the expected obligation on debt. In statistics, when information on the TLD's term structure is unavailable, the value close to maturity could then be assumed to be uniformly distributed between 0 and TLD, resulting in an expected value of TLD/2.

3.2 FCS Default Guideline

FCS (Farm Credit System) default guideline is summarized from two previous studies on credit risk model and default probability for farm lending (Barry et al 2004, Featherstone et al 2006). The credit score model was developed to distinguish between low credit risk (less financially constrained) and high credit risk (more financially constrained) farms. The model contains financial ratios recommended by the Farm Financial Standard Council, representing a farm's solvency, liquidity, repayment capacity, profitability, and financial solvency.

In the risk rating, each farm has five scores ranging from 1 to 10 on solvency, liquidity, repayment, profitability and efficiency accordingly. The five scores are then weighted to generate a final score between 1 and 10 by expression (9), where each farm is then grouped to a rating class with respect to the final score.

9)
$$\begin{aligned} \text{score} &= 30\% \times \text{solvency} + 20\% \times \text{liquidity} + 20\% \times \text{repayment} \\ &\quad + 20\% \times \text{profitability} + 10\% \times \text{efficiency} \end{aligned}$$

Generally, each risk rating is connected with a corresponding default rate. The risk rating definition, interval ranges, and implied default rates are illustrated in table 1.

3.3 Default Frequencies from Farm Records

Historical default frequencies are inferred from Farm Business Farm Management Association (FBFM) data that contains farm accounting information, such as income and cash flow statement, as well as farm reported market value on assets and liabilities during the period of 1995 to 2004. Consistent with Katchova and Barry (2005), farms with no debt are excluded, resulting in approximately 1,670 farms with 11,745 farm observations[4].

Following the default criterion and the notion for expected debt, a discrete time approximation of the nonparametric continuous-time hazard rate approach (cohort method) is adopted to infer marginal default rates from the FBFM data. The nonparametric approach was first proposed by Cutler and Ederer (1958) and has been commonly used by the rating agencies like Moody and Fitch Ratings for default and migrating analysis. A pool of farms, called a cohort, is formed on the basis of their risk ratings held in a given calendar year, and the default status for the farms of the cohort is

[4] A farm is removed completely from the panel if it has zero debt in any year. In total, 137 farms are excluded with a total of 650 observations.

tracked over some stated time horizon. In each time interval or horizon, some fraction of the cohort that has survived up to that time may default. The marginal default rate is the probability that a farm survived in the cohort up to the beginning of a particular time interval will default by the end of the time interval. The cohort method assumes that withdraws occur randomly during the interval, and the probability of survival/default at one interval, though conditional on surviving previous intervals, is independent of the probability of survival at the prior interval(s). Moreover, the interval is often set to be evenly distributed when long time data is available. For example, the default rates calculated by most rating agencies under the method are based on more than 30 years' annual or monthly observations. In this study, since only 10 years' annual data is available, the cohort spacing is selected based on data availability instead. In total, 9 cohorts are formed from the data with time interval ranging from 9 years to 1 year.

Consistent with the proposed default guideline, the farms are grouped with respect to their risk ratings defined above. Since relatively fewer farms are rated 7 and above, the farms with risk rating greater than 7 are grouped together, the 9 cohorts are then created for each of the 7 risk rating classes. The results are listed in table 2. Overall, average default rate across all cohorts for each risk rating class is lower than the corresponding value in table 1, which may be due to small sample size.

Loss-given-default (LGD) for each cohort is calculated as the average LGD for the defaulted farms by using reported market values on asset and the expected obligation in the next 12 months and a 10% recovery rate (Featherstone and Boessen 1994, Featherstone et al 1993). The average values on LGD across all cohorts for each rating class are also reported in table 2. On average, LGD is 23.91% for 1995-2004, which is similar to previous reported values on farm LGD. For example, Stam et al (2003) reported that average LGD for all farm loans issued by commercial banks, the FCS, life insurance companies and the Farm Service

Agency was 24.26% for 1995-2001. According to Federal Deposit Insurance Corporation (FDIC) [5], average LGD on farm loans issued by all commercial banks in Illinois is around 18.26% for 1995-2004.

3.4 Farm Panel and Summary Statistics

The following empirical analysis is based on a subset of the FBFM annual farm data. Since longer time range of data is better for revealing asset volatility and choice of capital structure, only farm records with a minimum time range of 10 years are included in the followed model estimation and prediction, resulting in 5,346 farm observations with 635 farms. Table 3 shows definition and summary statistics of some selected variables included in the study. The distribution for mean values of the variables by debt-to-asset ratio is listed in table 4.

On average, the log of asset-to-debt ratio for a typical farm is 1.38 with log of farm cash sale equal to 12.26. The tenure position and collateral ratio for the typical farm are 0.19 and 0.54 respectively. The ratio of depreciation over total assets for the farm is 0.005. In addition, a typical farm generally earns 5.1% on return on asset (ROA). The liquidity position for the typical farm is 0.57, and the ratios of net farm income (NETINC) and interest cost over value of farm production (VFP) are 0.20 and 0.10 respectively. The average age for the farm operator is 51.8. Since mean values for most of the selected variables are higher than their corresponding medians, above half farms are ranked low in values as compared to the typical farm.

In the table, we also report two normalized values of return on asset (ROA) and growth in total assets (GTA) for the typical farm, i.e. NROA and NGTA. For each farm record, NROA is obtained by rescaling return on asset by its standard deviation and the mean

[5] All FDIC insured institutions are required to file consolidated Reports of Condition and Income (Call Report) as of the close of business on the last day of each calendar quarter. FDIC constructed a database from the Call Report, and the database is publicly available on the website starting 1998.

value of NROA for the sample data is 1.26 while NGTA is calculated by dividing GTA by its volatility and it is 0.34 for the typical farm.

Table 4 illustrates a clear pattern of decreasing in tenure, age, NGTA, collateral ratio, liquidity and financial efficiency (NETINC/VFP) as debt-to-asset ratio increases on average, while size, INT/VFP and ROA moves in the same direction as debt-to-asset ratio increases. Although farms with asset value less than its total debt value on average have the highest ROA (0.08), their earnings must experience much larger variation as implied by the lowest value of NROA (0.79) than other farms and the average farm (table 4). These farms are largely composed of young leasing farmers, and have higher than average sale. Most of their debts could be non-collateralized as implied by the lowest collateral ratio (46.4%) for the group, and these farms are likely to take advantage of non-tax shield (0.007). Although these farms are characterized by total assets value less than total debts value, it is unclear whether any defaulted farms are included.

In addition, in calculating the standard deviations of ROA and GTA for each farm, a total of 10 records on farm asset and return are used. If there is any missing value, the missing value is replaced by imputed value through the multiple imputation method. The multiple imputation method was first introduced by Rubin (1987) to incorporate missing-data uncertainty, and has been widely used in survey data analysis (Schafer 1997, Schafer and Schenker 2000, Reilly 1993, Li 1988, and more). Rubin pointed out that when missing rates are low, highly efficient inference could be achieved with only a few imputations. Schafer and Schenker (2000, pp. 150) illustrated that multiple imputation “shows good coverage at all rates of missingness, even with only M=5 imputations”. For the farm panel data of interest, since the missing rate is about 16% percent, multiple imputation with number of imputations equal to 5 is used with missing values being replaced by the average imputed values through SAS MI procedure.

CHAPTER 4

CAPITAL STRUCTURE UNDER THE STRUCTURE MODEL: SUR MODEL AND TEST

As mentioned in the introduction, although elegant in theory, it is still not clear whether the structure model fits the farm household data and whether there are some other unrevealed factors determining farm financial position besides debt, asset return and its volatility. The chapter proposes an empirical model to test the structure model and theories of capital structures using farm panel data. Previous empirical studies on capital structure mainly support both pecking order theory and trade-off theory, while the studies on non-public firms revealed that the determinants of capital structure differ to some extent between the public and non-public firms. Thus, the study may provide further evidence to this observation.

4.1 Morton Model Based Linear Regression Model

From equation (4) and if we define $y_{it} = \ln \frac{A_{it}}{D_{it}}$ and $y_{it-1} = \ln \frac{A_{it-1}}{D_{it-1}}$, the expression can then be easily expressed as a linear regression model

10) $$\begin{aligned} y_{it} &= \beta_{i0} + \beta_{i1} y_{it-1} + \beta_{i2}\mu_i + \beta_{i3}\sigma_i^{\,2} + \varepsilon_{it} \\ &= x'_{it}\beta_i + \varepsilon_{it} \end{aligned}$$

in which x_{it} denotes a vector of independent variables and $x_{it} = (y_{it-1}, \mu_i, \sigma_i^{\,2})'$, and $\beta_{i\cdot}$ is a vector of parameters to be estimated.

In the model, log of asset-to-debt ratio, a measurement of farm's financial position, is the dependent variable that represents an underlying farm's choice of capital structure and is determined by farm characteristics. An equivalent measurement of the probability $\mathrm{P}(\mathrm{A}_{\mathrm{it}} \le \mathrm{D}_{\mathrm{it}})$ in expression (5) is then equal to

11) $$\mathrm{P}(\mathrm{A}_{\mathrm{it}} \le \mathrm{D}_{\mathrm{it}}) = P(\varepsilon_{it} \le -x'_{it}\beta_i) = \Phi(\upsilon_{it})$$

where $\upsilon_{it} = -x_{it}'\beta_i$.

Since the model allows x_{it} containing the lagged value of y_{it}, it is also a dynamic model. In a steady state for the farm, i.e. $t = t-1 = e$, its financial position can be written as

12) $$y_{ie} = \frac{\beta_{i0}}{1-\beta_{i1}} + \frac{\beta_{i2}\mu_i + \beta_{i3}\sigma_i^2}{1-\beta_{i1}} + \frac{\varepsilon_{ie}}{1-\beta_{i1}}$$

In this sense, a static model can then be adopted to address the steady state. On the other hand, if the estimate for lag of the log of asset-to-debt ratio in the dynamic model is not statistically significant, we may conclude that the farm are already in a steady state.

4.2 Issues in Empirical Estimation

Under the structure model, measurement of farm financial position generally relies on the joint normality of the latent variables, i.e. asset returns, which can be estimated from farm financial data. Gordy (2003, pp. 201, 203) pointed out that "the correlations across obligors in credit events arise due to common dependence on a set of systematic risk factors"; "regardless of their identity (of the risk factors), it is assumed that all correlations in credit events are due to common sensitivity to these factors". Crouhy et al (2000, pp. 78) did a comparison on the popular credit risk models, and pointed out that even in a simple bi-variate case, "the joint probability of default is in fact quite sensitive to pair-wise asset return correlations, and (this) illustrates the necessity to estimate correctly these (sample) data to assess precisely the diversification effect within a portfolio". Thus, a major concern about empirical application of the model is that the observed farm financial position for any two farms may be associated with each other due to asset correlation given the model assumption. On the other hand, when non-spherical disturbances appear in a linear regression model, ordinary least square (OLS) estimators will be inefficient although still unbiased and consistent; standard errors for the estimators are biased and inconsistent. Therefore, a proper linear regression model and corresponding estimation procedure should be introduced to address the issues.

Of the econometric models, the dependence structure can be captured by seemingly unrelated regression model (SUR). The model is a system of linear equations that are linked through the correlations among the errors, and has been used in studies of financial market (Campbell et al 1997). When farm panel is involved in the estimation, sample size can be reduced by statistical classification that still keeps similarities for individual farms or agents within each group. Thus by combining classification and SUR methods together with the structure model, we may then have an appropriate empirical econometric model that not only considers asset correlation but also in the meantime can take full use of farms' accounting information in describing potential risk at group level.

4.3 SUR Model with Unknown Correlation Matrix

In econometrics, seemingly unrelated regression model (SUR) is a technique for analyzing a system of multiple equations with cross-equation parameter restrictions and correlated error terms. When covariance matrix of disturbance is unknown, feasible generalized least square method (FGLS) can be applied to estimate the parameters and correlation coefficients simultaneously (Zellner 1962, Zellner and Huang 1962), while "the least squares residuals may be used (of course) to estimate consistently the elements of covariance matrix of disturbance" (Greene 2000, pp. 344).

Following Greene (2000), a SUR model can be written as

13) $$y_k = X_k \beta_k + \varepsilon_k \qquad k = 1, \cdots, M$$

where y_k is a vector of dependent variables, X_k is a $T \times L$ matrix with T being the total number of observations and L being the number of regressor, and M is the number of equations, the assumption about the error vector $\varepsilon = \left[\varepsilon'_{1,} \varepsilon'_{2,} \cdots, \varepsilon'_{M}\right]$ is

14) $$E[\varepsilon \mid X_1, X_2, \cdots, X_M] = 0$$
$$E[\varepsilon\varepsilon' \mid X_1, X_2, \cdots, X_M] = \Omega \qquad \Omega = \Sigma \otimes I$$

with Σ being the variance and covariance matrix. In the model, for the tth observation, the $M \times M$ covariance matrix of the disturbance is given by

15) $$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2M} \\ & \vdots & \vdots & \\ \sigma_{M1} & \sigma_{M2} & \ddots & \sigma_{MM} \end{bmatrix}$$

Given this, the stacked model with respect to expression (13) is

16) $$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ & \vdots & \vdots & \\ 0 & 0 & \ddots & X_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_M \end{bmatrix} = X\beta + \varepsilon$$

In estimating the parameters of the M equations, $T > L$ is required. For a known variance-covariance matrix, the general least square (GLS) estimator is given as following

17) $$\hat{\beta} = [X'\Omega^{-1}X]^{-1} X'\Omega^{-1}y = [X'(\Sigma^{-1} \otimes I)X]^{-1} X'(\Sigma^{-1} \otimes I)y$$

where $\Omega^{-1} = \Sigma^{-1} \otimes I$, in which $\otimes$ represents the Kronecker product. If the matrix is not unknown, it can be estimated by the regression residuals with the consistently estimated elements of $\hat{\Sigma}$ given by

18) $$\hat{\rho}_{jk} = \frac{e'_j e_k}{T} \qquad \mathrm{j, k} = 1, \ldots\ldots, \mathrm{M}$$

where e_i is the least square residuals from equation i.

Since farm records are often characterized by short time period and large number of farms, model for panel data is applied to groups of farms to increase the degree of freedom in the regression. Farms are grouped in terms of similarity, with each equation in the SUR model describing the corresponding farm group's choice of capital structure. By assuming that farms in the same group are identical, the observations in the group can be viewed as a sample derived from the same population.

In the empirical analysis of capital structure under the structure model, several variables that may have potential impact on a farm's choice of capital structure are considered, including the lagged value of log of asset-to-debt ratio, normalized ROA (NROA), farm size, growth opportunities, profitability, collateral position and non-debt tax shield. The first two variables, the lagged value of log of asset-to-debt ratio and NROA, are addressed by the structure model while the others are related to theories of capital structure. Consistent with Titman and Wessel (1988), this study uses the realized values for the explanatory variables as proxies of the value expected when the capital structure decision was made. If the empirical dynamic model is stable, the estimated coefficient of the lagged value of log asset-to-debt ratio should be less than 1. Moreover, a farm's asset-to-debt ratio is expected to be negatively effected by NROA if the farm tends to make offsetting adjustments in its capital structure in response to modifications of business risk as measured by the standard deviation of return on farm asset (Barry and Robison 1987, Gabriel and Baker 1980).

Given the variables, the full system of equations is then

19)
$$\begin{aligned}\ln\left(\frac{asset}{debt}\right)_{kt} =& \alpha_{kt}+\beta_{k1}\ln\left(\frac{asset}{debt}\right)_{kt-1} + \beta_{k2} NROA_{kt} + \beta_{k3} size_{kt} + \beta_{k4} NGTA_{kt} \\ &+ \beta_{k5}\, profit_{kt} + \beta_{k6}(collateral\quad ratio)_{kt} + \beta_{k7} shield_{kt} + \beta_{k8} tenure_{kt} + \varepsilon_{kt}\end{aligned}$$

for $k = 1,\cdots,M$ and $t = 1,\cdots,T$, where M and T denote number of equations (number of farm groups) and time period respectively.

Another major concern is that the structure model is dynamic, that is, it contains lagged values of the dependent variables in the predictors. For a dynamic panel data model, since the lagged dependent variable is correlated with the disturbance, within estimators (to remove serial correlation) are likely to be biased given small and fixed time period, and large cross-section sample size (Nickell 1981). For the reason, a semi-parametric three-stage least squares (3SLS) estimation method is proposed to allow independent variables containing lagged values of the dependent variable. Particularly, the paper will focus on the “feasible” instrumental variable within (IVW) estimators that “can be obtained by replacing the unknown conditional mean functions by some nonparametric estimators, say the nonparametric kernel estimators” (Baltagi and Li 2002, pp. 5). In the estimation, within transformation for the farm panel data is applied first using the kernel method and then the estimates are obtained through general 3SLS with the transformed data.

4.4 Within Transformation of Farm Panel Data and 3SLS Estimator

Within transformation of the farm panel is obtained by first expressing the SUR model in equation (19) into a form of semi-parametric dynamic panel data model

20) $$\mathrm{y_{it}} = x'_{it}\beta + \theta(z_{it}) + u_{it} \qquad \text{for } \mathrm{i} = 1,\cdots,\mathrm{N};\ \mathrm{t} = 1\cdots,\mathrm{T}$$

where

$$y_{it} = \ln(\frac{asset}{debt})_{it}$$
$$x_{1,it} = \left[\ln(\frac{asset}{debt})_{it-1}\right]$$
$$x_{2,it} = \left[NROA_{it}, size_{it}, profit_{it}, (NGTA)_{it}, (collateral \quad ratio)_{it,} shield_{it}, tenure_{it}\right]'$$
$$z_{it} = \left[NGTA_{it}, size_{it}, \ln(\frac{sale}{debt})_{it}\right]'$$

In the model, the independent variables are split into two parts as $x_{it} = (x_{1.it}, x'_{2,it})'$ with $x_{1,it}$ being the vector of endogenous variables and $x_{2,it}$ the vector of exogenous variables, and z_{it} is of dimension $d(=3)$, representing a vector of selected variables that are weakly exogenous in the sense that $E(u_{it} \mid z_{is}) = 0$ for $s \le t$, and $\theta(.)$ is a smooth function. Given this, the corresponding vector of instrumental variables is then $w_{it} = (w'_{1.it}, w'_{2,it})'$, with $w_{1.it} = E(x_{1,it} \mid z_{2,it-1})$ and $w_{2.it} = x_{2,it}$.

Following Baltagi and Li (2002), by taking the expectation of equation (20) conditional on z_{it} and then subtracting it from equation (20) gives

21) $$\mathrm{y}_{\mathrm{it}} - E(y_{it} \mid \mathrm{z}_{\mathrm{it}}) = (x'_{it} - E(x_{it} \mid z_{it}))'\beta + u_{it} \equiv v'_{it}\beta + u_{it}$$

Define $\hat{f}_{it} = (NTa^d)^{-1}\sum_{j=1}^{N}\sum_{s=1}^{T} K_{it,js}$ with $K_{it,js} = K((z_{it} - z_{js})/a)$, in which $K(\cdot)$ is the kernel function and *a* is a smoothing parameter, the conditional expectations of $y_{it,}$, $x_{it,}$ and w_{it} given z_{it} are

22) $$\begin{aligned}
&\hat{y}_{it} = \hat{E}(y_{it} \mid z_{it}) = (NTa^d)^{-1}\sum_{j=1}^{N}\sum_{s=1}^{T} y_{js}K_{it,js} / \hat{f}_{it} \\
&\hat{x}_{it} = \hat{E}(x_{it} \mid z_{it}) = (NTa^d)^{-1}\sum_{j=1}^{N}\sum_{s=1}^{T} x_{js}K_{it,js} / \hat{f}_{it} \\
&\hat{w}_{it} = (\hat{w}'_{1,it}, \hat{w}'_{2,it})' \text{ with} \\
&\quad w_{1,it} = \hat{E}(w_{1,it} \mid z_{i,t-1}) = (NT^d)^{-1}\sum_{j=1}^{N}\sum_{s=1}^{T} y_{j,s-1}K_{i,t-1,js} / \hat{f}_{i,t-1} \text{ and} \\
&\quad w_{2,it} = x_{2,it} - \hat{E}(x_{2,it} \mid z_{i,t-1}) = x_{2,it} - (NTa^d)^{-1}\sum_{j=1}^{N}\sum_{s=1}^{T} x_{2,js}K_{i,t-1,js} / \hat{f}_{i,t-1}
\end{aligned}$$

The within transformation of the data is then equal to

23) $$\begin{aligned}
&\tilde{x}_{it} = \hat{v}_{it} - T^{-1}\textstyle\sum_{s=1}^{T}\hat{v}_{is} \text{ with } \hat{v}_{it} = x_{it} - \hat{x}_{it} \\
&\tilde{w}_{it} = \hat{w}_{it} - T^{-1}\textstyle\sum_{s=1}^{T}\hat{w}_{it}, \\
&\tilde{y}_{it} = (y_{it} - T^{-1}\textstyle\sum_{s=1}^{T} y_{is}) \text{ - } (\hat{y}_{it} - T^{-1}\textstyle\sum_{s=1}^{T}\hat{y}_{is})
\end{aligned}$$

Empirical implementation of the transformation requires choosing the kernel function $K(\cdot)$ and also the value of the bandwidth *a*. Previous studies showed that a standard second-order kernel can be used if $d \le 3$, and "for any point-wise consistency of the nonparametric kernel estimators one only needs $a \to 0$ and $Na^d \to \infty$ as $\mathrm{N} \to \infty$" (Robinson 1988, Li and Stengos 1996, pp. 392). This study applies a uniform kernel of $K(u) = 0.5I(|u| \le 1)$ and the selection of bandwidth follows Silverman's rule of thumb, that is, $a = 0.9 \times s \times N^{(-1/5)}$ with *s* being standard deviation of the variable in $K(\cdot)$. Here, we calculated the bandwidth for the three variables included in z_{it}. Since the values are close, an average bandwidth of 0.18 is then applied in the estimation. With the transformed data, the empirical SUR model in expression (19) based on M groups is then written as

24) $$\tilde{y}_{kt} = \tilde{x}'_{kt}\beta_{ivw} + \varepsilon_{kt} \qquad k = 1\cdots M, t = 1\cdots T$$

where $\tilde{y}_{ik}$, $\tilde{x}_{ik}$ and $\varepsilon_{\mathrm{kt}}$ are defined similarly, and the vector of instrumental variables is given by $\tilde{w}_{ik}$. Finally, by applying general 3SLS to the within transformed farm panel will then generate "feasible" within estimator $\hat{\beta}_{ivw}$ for the SUR model.

4.5 Estimation Results and Inference

According to theory and previous studies, farm with greater asymmetric information should adhere more closely to the pecking order theory, agency theory and/or signaling theory. Following this opinion, the farms in the study are grouped by level of financial constraint. Grouping criteria in the past studies included degree of financial constraint, distinct business period, and public firm versus private firm (Barry et al 2000, Hubbard 1998, Schoubben and Hulle 2004). Since comparison of different business periods and/or farm types is not an option here, the farms in the study are grouped by degree of financial constraint, in which three split methods are applied, including debt to equity ratio, age of farmer, and application of the credit score model introduced in chapter 2. Farms with higher debt and lower equity (higher debt to equity ratio) or higher risk ratings are assumed to be more financially constrained, while older farmers is said to be less financially constrained than younger farmers.

Consistent with Barry et al (2000), the groupings are with respect to the values for the year (1995) prior to 1996-2004 estimation periods. For debt-to-equity ratio and age splits, the grouping will divide the farms into 10 groups, reflecting approximately 10% quantile of the sample population, while it is 7 groups with respect to risk rating. Accordingly, the SUR model of equation (24) then contains a system of 10 or 7 equations, each representing a group of farms. Farms of the same group are assumed to be identical, and there is equal number of observations in the panel.

The regression results for debt-to-equity ratio split are listed in table 5. The stability of the dynamic system is checked by the procedure of stability test (Greene 2000). Since the absolute values of the coefficients corresponding to lagged values of asset to debt ratio are less than 1, we conclude that the system is stable.

Of the variables suggested by the structure model, the effects of lag of asset to debt ratio and NROA are partly confirmed by the farm records. Lagged value of asset to debt ratio is negative for eight equations out of ten, and is significantly negative for three equations. The negative sign for the lagged value of asset-to-debt ratio implies that most farms appear to adjust to long run financial targets as the trade off theory predicts except for those highly financially constrained farms. On the other hand, NROA is significantly negative to the log asset to debt ratio for four equations. The negative relationship between NROA and log assets to debt ratio are consistent with previous findings that farmers tend to make offsetting adjustments in capital structure in response to changes in business risk (Escalante and Barry 2001, Yan et al. 2004).

Among the remaining variables related to capital structure theories, tenure has significantly positive impact on farms' financial position across all equations. The positive relationship shows that farms increase their debt targets as their leasing targets increase, which is consistent with the trade off theory. On the other hand, it also indicates that the non-depreciable characteristic of farmland implies relatively low cash flow and low debt carrying capacity of farmland ownership.

Farm size is significantly negative to the log of asset to debt ratio, as predicted by pecking order theory, as well as agency and signaling perspectives. It contradicts, however, the trade off theory. Moreover, the absolute values of the coefficients decrease as the magnitude of financial constraint increase, implying that more financially constrained farms adhere more closely to the pecking order theory and agency theory than do less financially constrained farms.

The significantly positive relationship between profit and log of asset to debt ratio across all equations again support both pecking order theory and agency perspective on capital structure. Since marginal contribution of the variable decreases gradually as farm financial constraint increases, it also suggests an ordered preference for the more financially constrained farms.

NGTA is significantly positive to the log of asset to debt ratio. The result is in line with trade off theory as well as agency and signaling perspectives, but it contradicts the pecking order theory. Finally, the coefficients for collateral ratio and shield are mixed, and most of them are not significant. Thus, we cannot draw a solid conclusion on the two variables.

The results by applying the age split and the credit score model split are listed in table 6 and table 7. Again, the results illustrate that the empirical dynamic model is stable, and the structure model is confirmed by most of the equations. Test results on theories of capital structure on average support both pecking order theory and trade off theory, which is consistent with previous studies, while it provides new supportive evidence on the agency theory. Moreover, the results clearly suggest that younger farmers adhere more closely to pecking order theory and agency theory than do older farmers. The same conclusion holds for higher risk farms.

CHAPTER 5

FARM CREDIT RISK MEASUREMENT: AN APPLICATION OF THE SUR MODEL

In the previous chapter, we proposed a SUR model to test the structure model and theories of capital structures. In this chapter, we try to apply the model to predict farm's ability to meet its financial obligation in the next 12 months by identifying the linkage between farm's financial position and credit risk. For the purpose, ratio of market value on farm asset to expected obligation is used as the dependent variable instead of leverage ratio, which may lead to change of determinants. The model is estimated with the same FBFM data at group level, and asset correlation is computed from the regression results. Farm default and joint default are then predicted by Gaussian copula based simulation process.

5.1 Variable Selection and Estimation

A farm's ability to meet its financial obligation within the next 12 months is also determined by the factors from the structure model and theories on optimal capital structure. Besides the variables from the structure model, the lagged value of log of asset-to-debt ratio and NROA, the following factors, associated with a farm's capital structure, are considered as potential determinants of the strength of fulfillment.

As indicated in the previous chapter, if additional financial need follows pecking order theory and/or agency theory, but farms in the FBFM data adjust to long term financial target of leverage ratio, the risk of falling short on its financial obligation in the near future would be positively influenced by profitability and tenure position while it would be negatively correlated to farm cash sale (size). The low debt carrying capacity of farmland also justifies the expected positive tenure effect.

The non-depreciation property of farmland implies higher liquidation value, and thus it would be much easier for a farm with higher collateral position to meet its obligation in the next 12 months than otherwise. In this sense, we would expect a positive relationship between farm collateral ratio and the dependent variable. On the other hand, if farms with large non-debt tax shield tend to include less debt in their capital structures as predicted by trade off theory, the ability to pay back in full will increase as non-debt tax shield increases. In the study, non-debt tax shield is measured by earning before depreciation divided by total assets instead of ratio of depreciation over farm total assets.

Farm's profitability is represented by log of value of farm production to debt ratio (VFP/Debt) and the ratio of net income to value of production (NETINC/VFP). Both variables measures a farm's profitability but in different ways. VFP/Debt is equivalent to log of cash sale to debt ratio (profit) in the previous chapter, while NETINC/VFP is associated with cost and called as financial efficiency. Since great value of NETINC/VFP could strengthen farms' risk-bearing capacity and thus lower risk of financial stress, it is expected to vary positively with the asset-to-expected debt ratio.

Farm balance sheet involves two major categories, current assets and liabilities, and intermediate and long-term assets and liabilities. Occurrence of financial distress may be due to mismatch of the categories that can be illustrated by liquidity position of a farm. To reveal the effect of liquidity position, a related variable measured by working capital over value of farm production (WC/VFP) is also included in the model and expected to have positive impact on a farm‘s ability to make timely payment, and thus stay liquid. It is noted that the three financial ratios, WC/VFP, NETINC/VFP and VFP/Debt, are usually employed by rating agencies and the credit risk model for farm lending, and can be called credit risk components. As in the previous chapter, the realized values for the explanatory variables are used as proxies of the values expected at the time when the ability to pay back was measured.

Table 8 presents a summary of the estimates and their corresponding standard errors for the model by each risk class. Overall, most of the variables are significant at better than the conventional level of 5%. In addition, the coefficients for lag of the dependent variables are all less than 1, indicating that the estimated dynamic model is stable.

Results show that the ability of paying back within next 12 months is negatively correlated to NROA, size and non-tax shield, while is positively effected by NGTA, tenure, collateral ratio, VFP/Debt (profit), WC/VFP and NETINC/VFP. The positive significant signs for the credit risk components suggest that the probabilities of a farm's ability to meet its current and anticipated financial obligations over the coming 12 months are associated with its liquidity, profitability as well as availability of secured assets. Of the variables suggested by theories on capital structure, the estimates for size, tenure, collateral ratio and profit are consistent with previous chapter. The results for collateral ratio support the agency theory while those for both collateral ratio and non-debt tax shield contradict the trade off theory although there is no consistent conclusion derived for both variables in the previous chapter, implying that the two attributes are more related to short-term financial decisions than long-term ones.

5.2 Asset Correlation and Robust Test

The correlation matrix for the SUR model is simultaneously estimated by equation (18) under the semi-parametric 3SLS. The estimated correlation is asset correlation under the period of 1995-2004 given the assumption that volatility of the model is from asset volatility based on the structure model. The estimated correlation matrix is listed in table 9. Overall, average correlation coefficient of the 7 risk rating classes is 20% with a standard deviation of 5.6%, which is clearly higher than the reported average asset correlation of 16% by KMV's risk classes (Lopez 2002). Since KMV's risk classification is for public firms, the result indicates that crop production is more likely to change toward the same direction than other industries, and thus comparatively the systematic risk plays a more important role in the production. In addition, the estimated correlation is also close to the reported intra-industry average asset correlation of 24.09% by Akhavein and Kocagil (2005). On the other hand, the average correlation is obviously higher than the reported value of 10.05% with a similar FBFM data by Katchova and Barry (2005), which is probably due to differences in regression model, estimation method and sample size.

It is noted that the matrix illustrates correlation between farm groups; the order of farm observations within each group is ignored. Thus, someone may question if the estimate truly represents population correlation between farms of different risk rating classes. To answer the question, two statistical tests, the log likelihood ratio test and the Jennrich's test for equality of correlation matrices, are adopted in the study.

The log likelihood ratio (LR) test is to test whether the correlation matrix is diagonal or not. If the estimated correlation matrix does not pass the LR test, implying that observations from any two different risk classes are independent, the problem of measuring credit risk would be much simplified than otherwise. Given the regression results for the SUR model, the likelihood ratio statistic is calculated by

25) $$\lambda_{LR} = T\left[\sum_{i=1}^{M} \log \hat{\sigma}_i^2 - \log\left|\hat{\Sigma}_{ML}\right|\right]$$

where $\hat{\sigma}_i^2 = \frac{e'e}{T}$ and is calculated from the least square estimation, and $\hat{\Sigma}_{ML}$ is the maximum likelihood estimate of the variance and covariance matrix for the regression. Under the null hypothesis of no asset correlation, the statistic has a limiting χ^2 distribution with M (M-1)/2 degree of freedom. In the study, M is the total number of equations in the SUR model and is equal to 7.

Jennrich's χ^2 test for homogeneity of two correlation matrices is proposed by Jennrich (1970). Let R denote the correlation matrix estimated by a sample of size n from a $p-$variate normal distribution with population correlation matrix $P=(r_{ij})$ and $P^{-1}=(r^{ij})$, the test statistic is then

26) $$J=\frac{1}{2}tr(Z^2)-dg'(Z)S^{-1}dg(Z)$$

with $Z=\sqrt{n}P^{-1}(R-P)$, $S=(\delta_{ij}+r_{ij}r^{ij})$ and δ_{ij} being the Kronecker delta. The null hypothesis is that there is no difference between the two correlation matrices. Under the null hypothesis, the test statistic has an asymptotic χ^2 distribution with p (p-1)/2 degree of freedom. In the study, the population correlation matrix is assumed to be the matrix from the SUR process and is illustrated in table 9 with p equal to 7.

Empirical testing applies Bootstrap techniques (Hollander and Wolfe 1999). A total of 5,000 random samples of residuals for each equation were drawn from the least square regression results for the SUR model. Each sample is randomly selected by the 7 risk classes or equations, and each class has 9 observations randomly picked out with one for each year in the sample. In each sampling run, the random sample is then used to compute a value of λ_{LR} and J respectively, in which the corresponding sample correlation matrix R is obtained by using expression (17). Both statistics are of χ^2 distribution with 21 degree of freedom. Overall, the mean value of λ_{LR} is 39.02 out of the total 5,000 calculated values, greater than the 1 percent critical value of 38.93. So the null hypothesis of diagonal for the correlation matrix is rejected, and thus asset correlation among farm risk classes is confirmed statistically[6]. On the other hand, the average value for J is 29.58 as compared to the same

[6] The LR test applied in the study is to test whether there is correlation among farms of different risk classes. As for the farms within each class, it is reasonable to assume that they are identical and are derived independently from the same population, but we did not test the assumption here.

critical value of 38.93, implying that statistically the order of farm observations within each group has no significant impact on the correlation matrix[7].

In conclusion, the estimated asset correlation matrix (table 9) represents population correlation, and can be used in the following simulation procedure to predict farm default and default correlation at group level.

5.3 Prediction of Default Probability and Default Correlation

As pointed out in the previous chapters, marginal probabilities of farm default are closely associated with asset correlation. A popular way to connect them is by copula approach (Nelson 1999). That is, given marginal distributions, we can derive correlation structure by choosing a copula, while given a copula, marginal probability of default for each agent can be predicted by simulation.

Of the copulas, Gaussian copula is fully characterized by correlation matrix Σ_G as multivariate normal distribution does. When time series data of farm assets are available, maximum likelihood estimate (MLE) of the elements of Ψ_G under Gaussian copula and the structure model is given by $\hat{\delta}_{ij} = \frac{\hat{v}_i'\hat{v}_j}{T}$, where $\hat{v}_i$ is a vector of estimates obtained by applying kernel density function to the corresponding value of normalized asset value from the structure model for farm i, and T is the total number of observations for the farm. On the other hand, for the correlation matrix Σ under the SUR model, the consistently estimated elements of $\hat{\Sigma}$ is equal to $\hat{\rho}_{ij} = \frac{e_i'e_j}{T}$, where e_i is the least square residuals from equation i.

Clearly, under the multivariate normal distribution assumption, $\hat{\rho}_{ij}$ from the SUR model is

[7] It is noted that the correlation matrix in table 9 is calculated using all the farm observations in each group while only 9 observations in each group is used to calculate the sampled correlation matrix in each sampling run. To account for any impact of sample size, we also did a similar test with sample size being considered. The testing result illustrates no such influence.

comparable to $\hat{\delta}_{ij}$ from Guassian copula. In this sense, marginal probabilities of farm default and joint defaults can be predicted by Monte Carlo simulation procedure for Gaussian copula with the estimated correlation in table 9.

The default simulation is at a time horizon of 1 year. In the simulation, the default threshold for any risk class or group is set to the quantile given by the historic default rates in table 1 or table 2 under the standard normal distribution. For example, for a default rate of 1.73% for group 7 in table 1, the default threshold is equal to $\Phi^{-1}(1.73\%) = -2.11$. In each simulation run, seven correlated random variables corresponding to each of the farm grouping are created by way of Cholesky decomposition given the estimated asset correlation matrix (table 9) (Bouyé et al 2000). Each random variable represents a generated asset values defined in equation (2) for the corresponding risk class, and a default will be registered if value of the random variable falls below its default threshold.

A total of 50,000 scenarios for each risk rating class are generated, and the default probability at group level is then defined as frequency of defaults out of the 50, 000 simulation runs. In addition, joint default probability is computed with a procedure similar to that for default probability in which joint default for any two farms is defined as concurrence of default for the two farms in a single simulating run. The default correlation is then computed by using expression (4) given the predicted marginal probabilities of default and joint default probabilities.

Predicted probabilities of default are listed in table 10. In the table, threshold 1 and threshold 2 correspond to the historic default rates in table1 and table 2 respectively. From table 10, the order of the predicted default probabilities under both default thresholds is consistent with the risk rating. Comparatively, the predicted default rates under threshold 1 (FCS default guideline) are relatively higher than those from threshold 2 (historical default benchmark from FBFM data). In addition, the predicted default rates are more close to their corresponding benchmark rates than otherwise. Overall, the weighted average default probability, weighted by the average debt in each group, is 0.895% for threshold 1 and is 0.643% for threshold 2. According to FDIC, the average default rate for the agricultural loans issued by commercial banks in Illinois is 0.83% for 1995-2004. Featherstone et al (2006) reported a default percentage of 1.83% for the loans issued by the Seventh District during 1995 to 2002, while Stam et al (2003) reported a default rate of 1.02% for agricultural banks[8] during 1995-2001. Obviously, the predicted default rates are close to those from FDIC and Stam et al (2003).

Table 11 illustrates the estimated default correlation inferred from the predicted defaults and joint defaults. Although asset correlation coefficients among the groups are around 20%, it is not surprising to observe that default correlation is much lower, implying that the two types of correlation matrices are not equivalent although both are closely associated. The result is consistent with a previous study by Crouhy et al (2000, pp. 78) who showed that for an asset correlation of 20% for two rated AA and B issuers by Moody's risk rating, the default correlation is only around 1.9%, and thus, "the ratio of asset returns correlations to default correlations is approximately 10-1 for asset correlations in the range of 20-60%". In addition, the joint defaults are more likely to occur among the higher risk groups. For example, when a farm of group 7 is in defaults, there is around 3% chance that another farm of group 6 will be also in default while the chance is less than 1% if "another farm" is from group 1 or group 2. These findings are consistent with a previous study by Hrvatin and Neugebauer (2004). The study found that of the same asset correlation of 25%, the derived default correlation is 3.5% between two issuers with default rates of 1% and 4% respectively, while it is 8.1% if the default rates for the two issuers are 4% and 10% respectively.

[8] A bank is defined as agricultural bank if its ratio of farm loans to total loans exceeds 14.97 percent (Stam et al 2003).

CHAPTER 6

AN ALTERNATIVE MEASUREMENT OF FARM CREDIT RISK: COPULAS APPROACH

In this chapter, two copulas, Gaussian copula and student t copula are used as an alternative in addressing farm asset correlation and predicting farm default. Maximum likelihood estimates (MLE) of the correlation matrix and/or degree of freedom are illustrated. Simulation process corresponding to the copulas will be introduced and applied for measuring farm credit risk under the structure model using the same FBFM data. Performance of the copulas is evaluated by Kolmogorov – Smirnov test.

6.1 Copulas

Copula, a function that maps the marginal distributions to the joint distribution, is an elegant way of describing dependence pattern. An important property of copula is its capability of capturing tail dependence, and thus has desirable advantage in default correlation analysis (Nelson 1999). There is increasing interest in applying copula-based approaches to correlation estimation and marginal probability prediction (Embrechts et al. 2003, Li 2000, Frey and McNeil 2003, Frey et al 2001, Hull and White 2001). Empirical application of copulas to the study of dependence pattern in credit risk measurement is still new in agricultural lending.

Following Nelson (1999), a copula is a function C of n variables on the unit n-cube with the following properties:

1. The range of C is the unit interval [0, 1];
2. $C(u)=0$ whenever $u \in [0,1]^n$ has at least one component equal to 0;
3. $C(u)=u_k$ if all coordinates of u are 1 except the k^{th} one;

4. C is n-increasing in the sense that for every $a \le b$ in $[0,1]^n$ the volume assigned by C to the n-box $[a,b] = [a_{1,} b_1] \times \cdots \times [a_n, b_n]$ is nonnegative.

As can be easily seen, a copula is in fact a multivariate distribution function with univariate margins restricted to the n-cube. Given a copula, asset correlation can be easily inferred from the empirical distribution of asset values. A powerful fact about copula approach is that it is not restricted to the normal distribution. Moreover, the copula approach is more flexible in choosing distributions such as t distribution. Application of the approach under the structure model may provide insight into credit risk measurement. Further, by comparing the estimates from different copulas, such as Gaussian copula vs. Student's t copula, we may test whether the joint normality assumption is appropriate for farm level data.

6.2 Asset Correlation: Gaussian Copula or Student's t Copula

For its simplicity in describing dependence structure and analytical tractability, Gaussian copula has been widely used in probabilistic modeling (Frey and McNeil 2003, Hull and White 2001, Li 2000). Following Bouyé et al (2000), let Φ_Σ be the standardized multivariate normal distribution with correlation matrix Ψ where Ψ is a symmetric, positive definite matrix with diag $\Psi = 1$, the multivariate Gaussian copula function is then defined as follows

28) $$C(u_1,\cdots,u_n \cdots,u_N;\Psi) = \Phi_\Psi(\Phi^{-1}(u_1),\cdots\Phi_n^{-1}(u_n),\cdots,\Phi^{-1}(u_n))$$

with $(u_1,\cdots,u_N)$ being a vector of random variables. The corresponding density is

29) $$c(u_1,\cdots,u_n,\cdots,u_N;\Psi) = \frac{1}{|\Psi|^{\frac{1}{2}}}\exp\left(-\frac{1}{2}x'(\Psi^{-1}\text{ - I})x\right)$$

with $x_n = \Phi^{-1}(u_n)$.). Log-likelihood function of Gaussian copula is given by

30) $$l(\theta) = -\frac{1}{2}\ln|\Psi| - \frac{1}{2}\sum_{t=1}^{T} x_t{}'(\Psi^{-1} - I)x_t,$$

where $x_t = \left(\Phi^{-1}(u_1^t), \cdots \Phi^{-1}(u_n^t), \cdots, \Phi^{-1}(u_N^t)\right)$ for $t = 1,2 \cdots T$, $\theta = \Psi$. According to Magnus and Neudecker (1988), the maximum likelihood (ML) estimate of the parameter Ψ under the function is then

31) $$\hat{\Psi}_{ML} = \frac{1}{T}\sum_{t=1}^{T} x_t' x_t$$

Clearly, the dependence pattern for a Gaussian copula is fully characterized by the correlation matrix like one for multivariate normal distribution, and the higher the value of pair-wise correlation, the stronger the dependence. It is noted that the dependence structure under the multivariate Gaussian copula might not be desirable for some sample data with large number of extreme values. Under the circumstance, Student's t copula may serve as a better alternative for its ability "to capture better the phenomenon of dependent extreme values, which is often observed in financial return data" (Demarta and McNeil 2005, pp. 1). Application of multivariate Student's t copula in this study will also test robustness of the structure model. The definition and log likelihood function for t copula is illustrated below (Bouyé et al, 2000).

Let $T_{\Lambda,v}$ be a standardized multivariate Student's t distribution with v degrees of freedom and a correlation matrix Λ , the multivariate Student's t copula (or t copula) function is then defined as

32) $$C(u_1, \cdots, u_n, \cdots, u_N; \Lambda, v) = T_{\Lambda,v}(t_v^{-1}(u_1), \cdots, t_v^{-1}(u_n), \cdots, t_N^{-1}(u_N))$$

with t_v^{-1} being the inverse of the univariate t distribution. The corresponding density is then

33) $$c(u_1, \cdots, u_n; \Lambda, v) = \left|\Lambda\right|^{\frac{1}{2}} \frac{\Gamma(\frac{v+N}{2})\left[\Gamma(\frac{v}{2})\right]^N}{\left[\Gamma(\frac{v+1}{2})\right]^N \Gamma(\frac{v}{2})} \frac{(1+\frac{1}{v}x'\Lambda^{-1}x)^{-\frac{v+N}{2}}}{\prod_{n=1}^{N}(1+\frac{x_n^2}{v})^{-\frac{v+1}{2}}}$$

with $x_n = t_v^{-1}(u_n)$, and the corresponding log-likelihood function is

34) $$l(\theta) \propto -\frac{1}{2}\ln|\Lambda| - \frac{(v+N)}{2}\sum_{t=1}^{T}\ln(1+\frac{1}{v}x_t{}'\Lambda^{-1}x_t) + (\frac{v+1}{2})\sum_{t=1}^{T}\sum_{n=1}^{N}\ln(1+\frac{x_n^2}{v})$$

where $x_t = \left(t_v^{-1}(u_1^t),\cdots t_v^{-1}(u_n^t),\cdots,t_v^{-1}(u_N^t)\right)$ for $t = 1,2\cdots T$, $\theta = (\Lambda, v)$.

In empirical analysis, the parameter Σ of Gaussian copula is often fitted by a two-step semi–parametric approach that consists of transforming the marginal observations into uniformly distributed vectors by using the empirical distribution functions first, and then estimating the parameter by maximizing the log–likelihood function given by expression (30), with the ML estimate being calculated using expression (31) (Genest et al 1995). As for t copula, since it is impossible to derive the ML estimate directly as for Gaussian copula, general iteration algorithm is adopted by taking the ML estimate for Gaussian copula as initial value i.e. $\hat{\Lambda}_0 = \hat{\Psi}_{ML}$. The recursive equation for computing the parameter is given by

35) $$\hat{\Lambda}_{m+1} = \frac{1}{T}(\frac{v+N}{v})\sum_{t=1}^{T}\frac{x_t'x_t}{1+\frac{1}{v}x_t'\hat{\Lambda}_m^{-1}x_t}$$

Repeating the process until convergence, i.e. $\hat{\Lambda}_{m+1} = \hat{\Lambda}_m$ as $m \to \infty$, gives the semi-parametric estimate of correlation matrix for the t copula.

It should be pointed out that the algorithm takes degree of freedom as given and does not allow estimating simultaneously the degree of freedom and the correlation matrix. To choose the best fitted combination of degree of freedom and the estimated correlation matrix, a log-likelihood ratio test is performed in this study. Suppose that the estimated correlation matrices under t copula are $\hat{\Sigma}_1$ and $\hat{\Sigma}_2$ respectively for any two values of degree of freedom, say v_1 and v_2, the test statistic is given by

36) $$LR = -2(l(\hat{\theta}_1) - l(\hat{\theta}_2))$$

where $\hat{\theta}_1 = (v_1, \hat{\Lambda}_1)$, $\hat{\theta}_2 = (v_2, \hat{\Lambda}_2)$, $l(\cdot)$ denotes the log-likelihood function given by expression (34). The test statistic follows χ^2 distribution under the null hypothesis of equal parameters with degree of freedom equal to (v_1 - v_2) for $v_1 > \mathrm{v}_2$.

Empirical estimation of asset correlation directly uses the structure model given by equation (1) with the same FBFM data and grouping criteria in chapter 4 and chapter 5. In the estimation, empirical cumulative distribution function (CDF) of farm asset returns is derived first by using kernel density estimation. The bandwidth *a* for each farm's time series observations is selected by Silverman's rule of thumb, that is, $a = 0.9 \times s \times N^{(-1/5)}$ with s being the standard deviation of the variable for the corresponding kernel function and N=10. Since the correlation is for farm groups instead of individual farms, asset correlation under Gaussian copula assumption is estimated by bootstrap (Hollander and Wolfe 1999). A total of 5,000 samples are selected. In each sampling process, 7 farms with one for each group are randomly picked out and a correlation matrix is then calculated accordingly. The final correlation matrix is set equal to mean of all the obtained matrices.

With the estimated correlation matrix for Gaussian copula, the correlation matrix for t copula is then obtained by similar sampling process. In each run of the process, a set of degree of freedom (*df*) from 1 to 20 is adopted to run the algorithm for t copula, resulting in a total of 20 estimated correlation matrices and their corresponding log likelihood values $l(\theta)$ with one for each degree of freedom. The mean values of the log likelihood values out of the 5,000 samples are then used to compute the LR statistics to test each pair of correlation matrix and degree of freedom. The test shows that the desired degree of freedom (*df*) is 6, which is consistent with a previous study given by Breymann et al (2003) on t copula. The estimated correlation matrix with *df* of 6 will then be used for default simulation under t copula.

Mean values of the correlation coefficients for Gaussian and t copulas are listed in table 12; their corresponding correlation matrices are listed in table 13. It is noted that the estimated correlation is for the period of 1995-2004.In table 12, the mean value of correlation coefficients is 10.8% with a standard deviation of 9.1% for Gaussian copula, and is 11% with a standard deviation of 8.3% for t copula. Table 13 illustrates that the pair-wise correlation coefficients from t copula are comparatively higher than those from Gaussian copula. Overall, average asset correlation from the copulas is around 11%, close to a reported value of 10.5% from a single factor model (Katchova and Barry 2005), but is obviously lower than that of 20% from the SUR model showed in table 9.

6.3 Simulation and Prediction

When copula is derived from a multivariate Gaussian copula or t copula, it turns out to be easy to simulate pseudo random variables admitting such dependence structure (Schmidt 2007, Bouyé et al 2000). In the structure model, normalized asset values in expression (5) is a random variable, and a farm is predicted in default if the value of its normalized asset value is less than a historic default value or threshold. Under Gaussian copula assumption, the following algorithmic steps are adopted to generate the full distribution of the portfolio credit risk at a time horizon of 1 year.

1. Derivation of default threshold for each farm in the portfolio.
2. Estimation of correlation coefficient between each pair of obligators' asset values.
3. Generating of asset value scenarios from joint normal distribution, first applying the Cholesky decomposition to the correlation matrix, and then pre-multiplying the decomposed matrix to the generated vector of random variables from standard normal distribution. Each scenario represents a vector of normalized

asset values illustrated by equation (2), one for each of the N (for example) obligors in the portfolio.

4. For each scenario and for each obligor, the generating value is compared to its corresponding default threshold given by step 1, and a default will be registered if the value falls below the threshold.
5. By repeating the procedure a large number of times, say 10, 000 times, a default sample for the underlying portfolio is acquired, where the default probability for each agent is calculated as frequency of defaults out of the total number of simulation runs.

The prediction process for t copula is almost the same as that for Gaussian copula with just one exception. The estimated correlation matrix and desired degree of freedom for t copula are used in step 2, in which the generated random variables are adjusted first by the matrix from Cholesky decomposition, and then by the degree of freedom and finally by a set of random variables generated from chi-square distribution with the same degree of freedom. Given the probabilities of default from simulation, and assuming that default event follows Bernoulli distribution, default correlation for any two farm groups is then calculated by equation (6).

The marginal probabilities of default corresponding to the estimated correlation matrices are predicted for each group by simulation with a time horizon of 1 year in which a total of 50,000 scenarios on the normalized asset values are generated. The joint probability of default for any two groups is also computed with the simulation results; then their default correlation is obtained. The two types of default thresholds adopted are the same as those used for predicting default rates under the SUR model (table 1 and table 3). The predicted probabilities of default (PD) from the two copulas and their corresponding default correlation are listed in table 14 and table 15 respectively.

Table 14 illustrates that with the same default threshold, the predicted probabilities from Gaussian copula are obviously higher than those from t copula. For example, under the default threshold 1, the weighted average default probability is 0.73% for Gaussian copula with only 0.40% for t copula. In addition, given the same debt level, the weighed average default rates under default threshold 1 are comparatively higher than those under default threshold 2 regardless of Gaussian copula or t copula. Overall, the predicted average default rate from Gaussian copula are close to 0.83% by FDIC for 1995-2004, but is clearly lower than 1.02% by Stam et al (2003) and 1.83% by Featherstone et al (2006)

As expected, the estimated pair-wise default correlation in table 15 is lower than the corresponding asset correlation listed in table 13. Default correlation tends to occur more often between high risk rating groups than others. For example, although the average asset correlation among the lowest three risk rating group is around 10% under either copula, the corresponding default correlation is almost negligible. The results are consistent with previous observations on the relationship between asset correlation and default correlation. Moreover, the estimated default correlation under t copula is obviously higher than that for Gaussian copula. For example, under Gaussian copula and default threshold 1, the average default correlation between risk rating 6 and 7 is less than 2%, while the value is 7.4% under t copula.

6.4 Selection of Copulas: Kolmogorov-Smirnov Test

To evaluate the performance of the two copulas in modeling dependence with farm records, Kolmogorov-Smirnov test is used (Hollander and Wolf 1999). By the test, we can determine which copula, Gaussian or Student's t, better fits the data. For example, for two series of random variables x and y with cumulative distribution function $F(x)$ and $F(y)$, the Kolmogorov- Smirnov statistic is given by

37) $$D = \sup \left| F(x) - F(y) \right|$$

The null hypothesis for the same sequence is rejected at level α if $\sqrt{\frac{n}{2}} D > K_{\alpha}$ with K_{α} being the corresponding critical value and n the sample size.

In the study, the D statistic is calculated by comparing the observed values given by equation (5) to their corresponding predicted values from simulation. Two series of the predicted values, one for Gaussian copula and the other for t copula, are generated from 50,000 simulation runs. For each group and a selected copula, the predicted value is represented by mean of the total simulated values.

The test statistic is 0.267 for Gaussian copula, and is 0.801 for t copula. The 1 percent critical value is 0.80, and thus the null hypothesis cannot be rejected for Gaussian copula, but is weakly true for t copula, implying that the predicted values by copulas are statistically indifferent from the observed values directly derived from the structure model. Comparatively, Gaussian copula performs better in fitting the sample data. The results also justify the usage of Gaussain copula estimation method in practice.

CHAPTER 7

EXPECTED LOSS AND UNEXPECTED LOSS

Given probability of default, loss-given-default, and default correlation matrix, the expected loss (EL) and unexpected loss (UL) for the farm portfolio is then computed by mean-variance method given by equation (6). The EL and UL at portfolio level from the SUR model and copulas approach at a 1-year horizon are listed in table 16 and Figure 2.

Comparatively, the predicted expected loss and unexpected loss from the SUR model and under the default threshold 1 are higher than other combinations (table 6). Since the estimated default correlations are close under the two thresholds, the high value are more likely due to difference in the predicted PD and default benchmark. Overall, the average expected loss for a typical farm portfolio under the SUR model is 0.19% while it is 0.15% under Gaussian copula and is 0.08% under t copula. The corresponding predicted average unexpected loss is 0.98% for the SUR model with 0.86% for Gaussian copula and 0.68% for t copula (Figure 2). The reported average loan loss allowance (EL) for agricultural banks at a national level during 1995-2001 is around 0.33% (Stem et al 2003). According to FDIC, the average loss for agricultural loans issued by commercial banks in Illinois is 0.18% for 1995-2004. Overall, the predicted values of EL at portfolio level are all lower than the reported value by Stem et al (2003), while the predicted EL by the SUR model is close to the reported value by FDIC when compared to those by copulas, especially t copula. Besides the difference in sample periods, farm type and reported region, the distinct estimation method for asset correlation is likely to be the reason.

The data period for estimation of farm asset correlation and prediction of EL and UL is for 1995-2004. The same period should be considered in comparison. According to FDIC, the average default rate of agricultural loans issued by commercial banks in Illinois is

0.84% for 1995-2004, 0.74% for 1995-2007 and 0.49% for 2005-2007, while the corresponding EL are 0.18, 0.14% and 0.04% respectively. Obviously, the predicted average PD and EL under the SUR model are close to the historical average values of the period 1995-2004, the same period for the sample data.

It is noted that the reported EL and PD by Stem et al (2003) is at a national level and for 1995-2001 while the prediction in the study focus on farms in Illinois and most of them are grain farms. In this sense, it is not surprising to see the difference.

Although both the SUR model and the copulas approach are based on the structure model, the SUR model considers more factors than the structure model does. The prediction results seems to support the observations by Ericsson et al (2005) and Caouette et al (1998) that the under-prediction/fitting of the structure model is likely due to factors not included in the structure model rather than the model itself.

The SUR model is like Gaussian copula in adopting multivariate normal distribution of farm asset. On the other hand, the two approaches are empirically used to capture asset correlation from the same FBFM data and then to predict farm credit risk under the same simulation process, risk classification and default thresholds. In this sense, the approaches are comparable and the comparison would provide some insights on how different approaches would impact the risk prediction. The estimated asset correlation and default correlation by the two approaches are summarized in table 17.

Table 17 illustrates that the pair-wise asset correlation from the SUR model is higher than that from the Gaussian copula approach. Although the inferred pair-wise default correlations among the lowest three risk-rating groups are similar, those between high-risk groups are different and with clearly higher values under the SUR model. For example, the asset correlation between group 6 and 7 under Gaussian copula is 11% with an inferred default correlation of 1.8% while the values corresponding to the SUR model are 12.8% and

3.0% respectively. The higher value in asset correlation and default correlation under the SUR model are likely to induce higher predicted PD, EL and UL as showed earlier in this chapter. The comparison indicates that asset correlation had a significant influence on prediction of farm default, default correlation and loss. Moreover, under the SUR model, the correlation matrix is estimated by using all the farm observations within each risk rating class. As contrast, under Gaussian copula the correlation matrix is estimated by bootstrap method in which only 10 observations for each farm group are used in each sampling process. And thus, short time series observations for the involved farms may be another reason for the relatively lower estimated asset correlation under the copulas approach.

CHAPTER 8

CONCLUSION

As the regulatory requirements are moving towards economic-based measures of risk, banks are urged to build sound internal measures of credit risk, in which prediction of a borrower or group of borrowers' credit risk plays a dominant role. The study addresses problems in measuring credit risk under the structure model, and then proposes a seemingly unrelated regression model (SUR) to test applicability of the model as well as theories of farm capital structure in explaining farms' choice of financial position. The empirical model is then used to predict farms' ability in meeting their current and anticipated obligations in the next 12 months. The empirical model accounts for both the dependence structure and the dynamic feature of the structure model.

The SUR model is adopted for estimating the asset correlation using FBFM data over 1995-2004. The correlation is also estimated by Gaussian copula and t copula approaches with the same FBFM data for comparison. With the estimated asset correlation, farm risk is then predicted by copula based simulation process in which FCS default guidelines and historical default rates from the farm records are used as default thresholds, where default is defined and used for investigating the historical default rates.

Regression results indicate that the empirical dynamic model is stable, and the structure model is confirmed by most of the farm records. Consistent with previous studies, the results show significant support for the pecking order theory of farm financial structure relative to trade off theory. They also provide new supportive evidence on the agency theory. Moreover, farms with greater asymmetric information problems adhere more closely to pecking theory and agency theory.

Empirical results also indicate that a farm's ability to meet its current and anticipated financial obligations in the next 12 months is associated with those factors related to the structural model, theories of farm capital structure, and credit scoring models.

The estimated asset correlation is 20% by the SUR model and is 11% by the copula approach. Apart for difference in methodology for estimating asset correlation**,** the relatively lower estimated asset correlation under the copulas approach is more likely due to short time series observations for the involved farms in the sampling process. The predicted default correlation by either approach is lower than the corresponding asset correlation. Comparatively, the predicted probability of default and expected loss at portfolio level by the SUR model are close to reported values for the same period of 1995-2004 and same region.

Results indicate that the predicted probabilities of default at high-risk groups are higher than the corresponding FCS default guideline under Gaussian copula (Figure 3). In this sense, farm rating by the structure model based copula approach differs from those by the credit score model, which maybe characterized by the copula approach. For example, some farms were grouped into group 5 by their own credit scores should be actually be classified as group 6 by the predicted default rate. This is also true by the SUR model, and the deviation at high-risk groups is even larger.

The results illustrate that the methods used in the study can be also applied to agricultural lending using available farm records, which provides a solution to the two major issues in risk assessment for agricultural lending, i.e. lack of long-time loss data and limited information of macroeconomic factors on changes of farm assets.

The study has important implications in farm credit risk management under the Basel II. First, this is the first study that addresses asset correlation and default correlation among risk classes in agricultural lending. The results provide a guideline for portfolio management of the agricultural lending institutions. Second, although the study focuses on model testing, application and comparison, the approaches introduced in the study are applicable to farm credit risk management. For example, given a farm’s accounting information, we can use one of the equations say the equation for group 5 in the SUR model to estimate its asset-to-expected debt ratio. By comparing the estimated value to the group confidence intervals, we can statistically examine whether the farm belongs to group 5 or not. Third, dependence structure as well as level of the dependence for farm assets has significant impact in measuring farm credit risk, and thus should be emphasized in loan pricing and in risk diversification. Finally, asset correlation as well as default correlation may change under different business cycles. Application of the approaches should pay attention to possible changes in economic factors and update the information accordingly.

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FIGURES AND TABLES

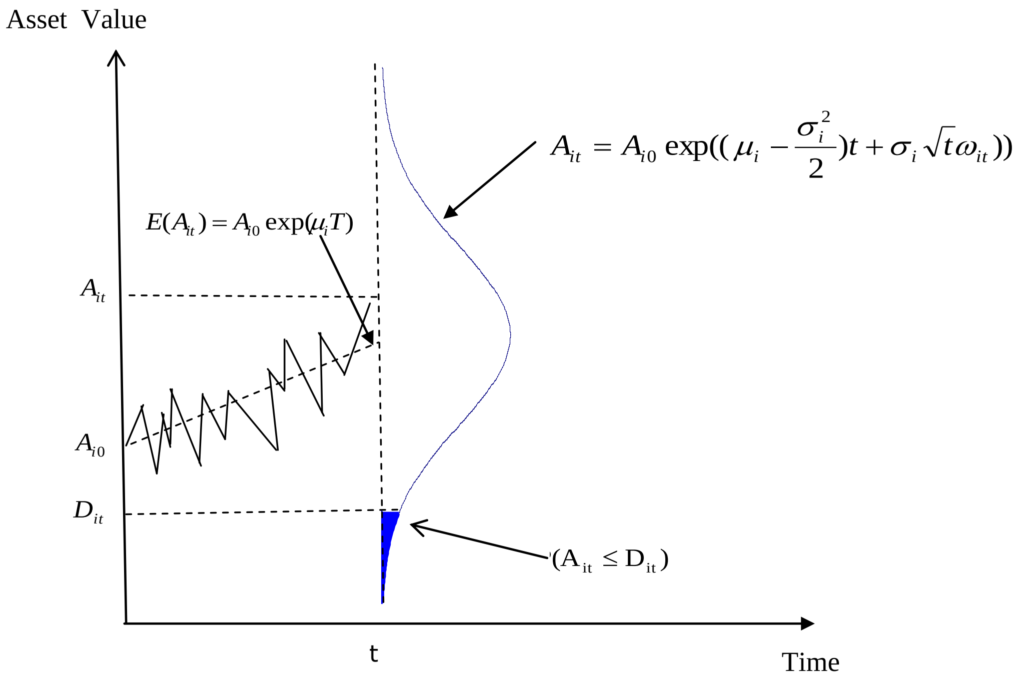

Figure 1 Distribution of the Farm's Asset Value

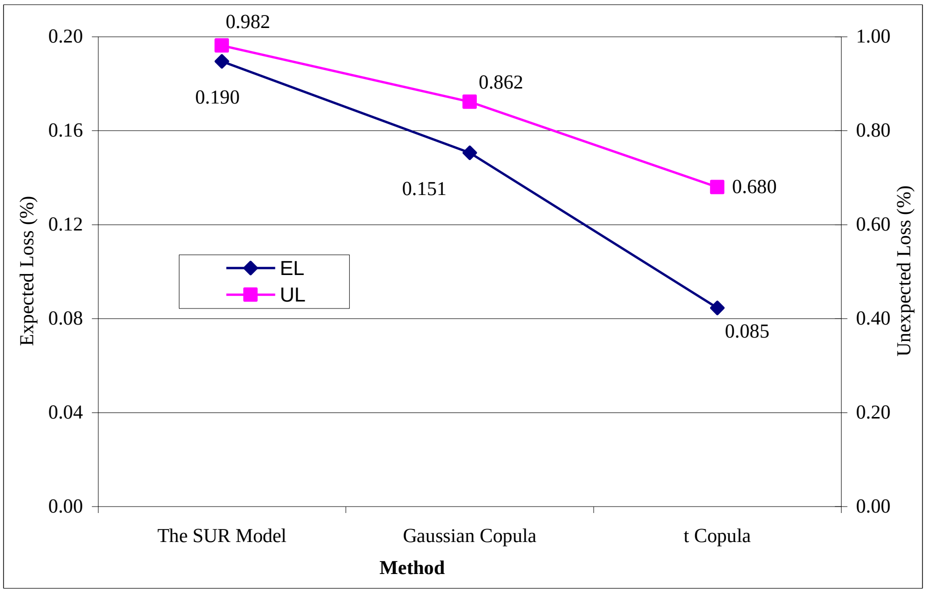

Figure 2 Overall Estimated Expected Loss (EL) and Unexpected Loss (UL)

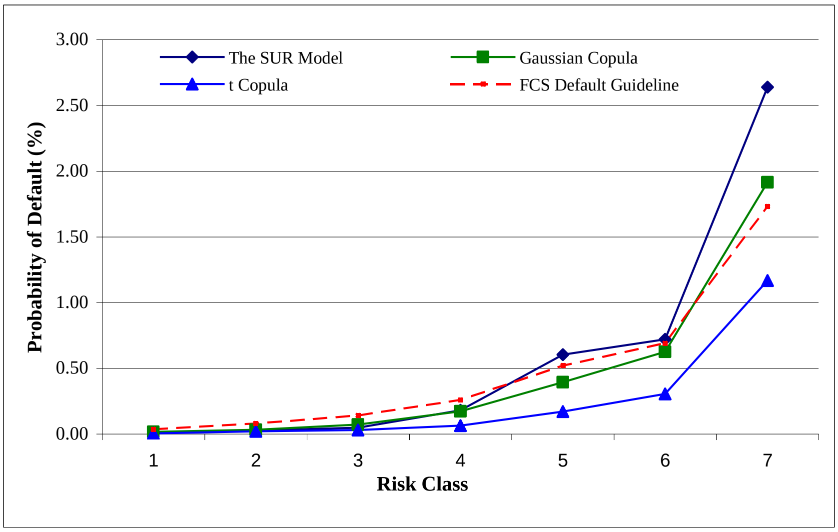

Figure 3 Predicted Average PD by the SUR Model and Copulas vs. FCS Default Guideline

Table 1 Credit Scoring Model and Proposed Probability of Default (PD) by Farm Credit System

Risk Rating Class	Proposed PD Guidelines (%)	FCS Guidelines	Solvency	Liquidity	Repayment	Earnings	Efficiency
			Equity to Assets Ratio	Current Debt Ratio	CDRC* Ratio	Return on Assets (%)	Gross Farm Return Ratio
1	0.00-0.035	AAA to AA	>0.80.	> 2.5	> 1.6	>10	> 0.4
2	0.035-0.08	AA to A	0.75-0.80	2.00-2.50	1.50-1.60	8-10	0.25-0.40
3	0.08-0.014	A to A-	0.70-0.75	1.80-2.00	1.40-1.50	6-8	0.30-0.35
4	0.14-0.26	BBB+ to BBB	0.65-0.70	1.60-1.80	1.30-1.40	4-6	0.25-0.30
5	0.26-0.52	BBB to BBB-	0.60-0.65	1.40-1.60	1.20-1.30	2-4	0.20-0.25
6	0.52-0.69	BB+	0.50-0.60	1.20-1.40	1.10-1.20	0-2	0.15-0.20
7	0.69-1.145	BB+ to BB	0.40-0.50	1.00-1.20	1.00-1.10	-2-0	0.10-0.15
8	1.145-1.73	BB to BB-	0.30-0.40	0.80-1.00	0.901-1.00	-4 - -2	0.05-0.10
9	1.73-2.88	BB- to B+	0.20-0.30	0.60-0.80	0.80-0.90	-6 - -4	0.00-0.10
10	2.88 and up	B and down	< 0.2	< 0.5	< 0.80	< -6	< 0

*CDRC ratio= (farm and nonfarm net income + depreciation+ debt service-annual family expenditures-income taxes)/debt services

Source: Farm Credit System risk-rating guidelines definitions (Featherstone et al (2000)) and Credit Risk Rating Systems: Tenth Farm Credit District (Barry et. al)

Table 2 Historical Default Frequency and Loss-Give-Default (LGD) of FBFM Farms (1995-2004)

Risk Rating Class	Cohort 1 (1995-2004)		Cohort 2 (1996-2004)		Cohort 3 (1997-2004)		Cohort 4 (1998-2004)		Cohort 5 (1999-2004)		Cohort 6 (2000-2004)		Cohort 7 (2001-2004)		Cohort 8 (2002-2004)		Cohort 9 (2003-2004)		Average Default Rate	LGD
	# of Farms	Default Rate	# of Farms	Default Rate	# of Farms	Default Rate	# of Farms	Default Rate	# of Farms	Default Rate	# of Farms	Default Rate	# of Farms	Default Rate	# of Farms	Default Rate	# of Farms	Default Rate		
1	179		236		134		21		69		116		41		42		118			
2	146		183		198		105		182		193		153		155		205			
3	130		145		173		91		169		176		141		131		183			
4	130		148		184		154		182		223	0.45%	166		155		206		0.05%	22.94%
5	126		125	1.60%	149		210		243		205		196		181	0.55%	188		0.26%	23.29%
6	110	0.91%	90		134	0.75%	193		185	0.54%	159	0.63%	186		197		128	0.78%	0.44%	23.69%
7	113	1.77%	84	4.76%	162	1.85%	384	0.78%	324	0.31%	210	1.43%	347	0.29%	378	1.06%	185	1.62%	1.54%	25.71%

Table 3 Basic Statistics for Selected Variables of FBFM Farms (1995-2004)

Variable	Description	Mean	Median	Standard Deviation
Log (asset to debt ratio)	Log of (total assets to total liabilities ratio)	1.38	1.20	0.80
Size	Log of farm cash sale	12.26	12.27	0.60
ROA	Return on asset	0.051	0.043	0.075
NROA	Return on asset divided by its volatility	1.27	1.16	1.28
Tenure	Owned land over total tillable land	0.19	0.11	0.22
Collateral ratio	Machinery & equipment plus farmland value over total assets	0.54	0.55	0.16
Shield	Depreciation to total assets ratio	0.005	0.004	0.006
Liquidity	Working capital over value of farm production (VFP)	0.57	0.36	1.08
NETINC/VFP	Netfarm income over VFP	0.20	0.21	0.16
Age	Age	51.8	51	11
INT/VFP	Interest expense and accrued interests over VFP	0.100	0.081	0.084
NGTA	Annual growth in total assets (GTA) divided by its volatility	0.34	0.21	0.95

Table 4 Distribution of Selected Variable Means by Debt-to-Asset Ratio

Variables	Size	ROA	NROA	Tenure	Age	Collateral ratio	Shield	Liquidty	NETIN C/VFP	INT/VFP	NGTA	Farm Obs.
D/A <= 0.2	12.21	0.047	1.25	0.256	53.56	0.540	0.0032	1.019	0.271	0.044	0.361	1,585
0.2< D/A <=0.25	12.24	0.050	1.26	0.222	51.04	0.551	0.0064	0.526	0.233	0.083	0.349	522
0.25< D/A < 0.3	12.32	0.057	1.42	0.191	49.72	0.555	0.0068	0.436	0.229	0.102	0.342	535
0.3 < D/A <=0.35	12.34	0.052	1.30	0.167	48.16	0.555	0.0067	0.295	0.203	0.113	0.345	518
0.35 < D/A <=0.4	12.29	0.056	1.23	0.160	47.71	0.542	0.0071	0.196	0.193	0.128	0.330	459
0.4 < D/A <=0.5	12.40	0.059	1.31	0.136	46.85	0.543	0.0068	0.094	0.172	0.137	0.352	767
0.5< D/A <=0.6	12.47	0.066	1.26	0.130	46.15	0.526	0.0075	-0.010	0.151	0.148	0.401	509
0.6< D/A < 0.7	12.46	0.058	1.12	0.102	47.72	0.524	0.0078	-0.106	0.120	0.158	0.228	308
0.7 < D/A <=0.8	12.32	0.071	1.11	0.077	47.13	0.474	0.0066	-0.176	0.150	0.163	-0.017	99
D/A > 0.8	12.58	0.080	0.80	0.053	46.11	0.464	0.0069	-0.233	0.137	0.153	-0.115	44
Total	12.26	0.051	1.27	0.186	51.78	0.539	0.0050	0.570	0.210	0.100	0.340	5,346

D/A =debt to asset ratio

Table 5 1996-2004 Estimation Results for the Seemingly Unrelated Regression Model by Operator Debt-to-Equity Ratio Splits

Group / Variable	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Group9	Group10
Log (lag of assets to debt	-0.032	-0.17***	-0.233**	-0.067	-0.478**	-0.261	-0.537	-0.493	0.167	0.248
ratio)	(0.06)	(0.10)	(0.12)	(0.44)	(0.20)	(2.40)	(7.30)	(0.57)	(0.71)	(0.36)
NROA	-0.004	-0.047*	-0.016***	-0.012***	-0.008	-0.008	-0.004	0.004	-0.014**	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Size	-0.478*	-0.284*	-0.255*	-0.214*	-0.184*	-0.181*	-0.154*	-0.127*	-0.086*	-0.067*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
NGTA	0.057*	0.047*	0.048*	0.034*	0.021*	0.028*	0.025*	0.022*	0.019*	0.015*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Tenure	0.823*	0.375*	0.322*	0.661*	0.651*	0.370*	0.753*	0.211*	0.363*	0.261*
	(0.06)	(0.07)	(0.08)	(0.09)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
Profit	0.793*	0.667*	0.646*	0.494*	0.461*	0.336*	0.381*	0.219*	0.251*	0.163*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Collateral Ratio	-0.022	0.035	0.629*	0.011	-0.099*	0.185**	-0.016	-0.120***	0.049	0.089
	(0.09)	(0.09)	(0.12)	(0.10)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)
Shield	-0.722	-3.66*	-1.395	1.016	-1.625***	-1.276	-0.337	0.603	-1.676***	0.007
	(1.58)	(1.50)	(1.32)	(1.27)	(0.91)	(1.04)	(1.25)	(1.20)	(1.04)	(0.72)
R-square	0.7444									

Note: single, double and triple asterisks (*) denote significance at 1%, 5% and 10% confidence level respectively

Table 6 1996-2004 Estimation Results for the Seemingly Unrelated Regression Model by Operator Age Splits

Variable \ Group	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Group9	Group10
Log (lag of assets to debt ratio)	0.089	0.055	-0.828	-0.025	-0.121	-0.288***	0.085	-0.237	-0.407**	-0.024
	(0.15)	(0.11)	(0.59)	(0.13)	(0.09)	(0.19)	(0.13)	(0.17)	(0.24)	(0.07)
NROA	0.001	-0.007	-0.005	-0.002	-0.018*	-0.004	-0.034**	-0.022*	-0.018**	-0.019**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.181*	-0.258*	-0.281*	-0.284*	-0.305*	-0.275*	-0.319*	-0.236*	-0.426*	-0.520*
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
NGTA	0.022*	0.036*	0.046*	0.045*	0.049*	0.047*	0.055*	0.057*	0.066*	0.072*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tenure	0.580*	0.703*	0.760*	0.920*	0.923*	1.123*	1.277*	0.881*	0.810*	0.348*
	(0.06)	(0.09)	(0.09)	(0.12)	(0.11)	(0.10)	(0.10)	(0.09)	(0.07)	(0.07)
Profit	0.408*	0.588*	0.559*	0.616*	0.647*	0.648*	0.768*	0.653*	0.740*	0.778*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Collateral Ratio	0.226*	0.052	0.050	0.242*	-0.298*	-0.020	-0.278**	0.220**	0.222**	0.116
	(0.08)	(0.10)	(0.10)	(0.09)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)
Shield	0.161	-0.007	-0.099	-0.074	0.508	-0.498	-2.344***	-4.098*	-1.022	-2.656
	(0.90)	(0.89)	(1.53)	(1.49)	(1.13)	(1.73)	(1.33)	(1.75)	(1.61)	(1.93)
R-square	0.6789									

Note: single, double and triple asterisks (*) denote significance at 1%, 5% and 10% confidence level respectively

Table 7 1996-2004 Estimation Results for the Seemingly Unrelated Regression Model by Operator Credit Score Splits

Variable / Group	Group1	Group2	Group3	Group4	Group5	Group6	Group7
Log (lag of assets to debt ratio)	-0.207*	-0.340*	0.017	0.095	0.055	0.334**	-0.208
	(0.06)	(0.13)	(0.11)	(0.08)	(0.10)	(0.10)	(0.37)
NROA	-0.016**	-0.025*	-0.019**	-0.012**	-0.004	0.001	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.364*	-0.306*	-0.207*	-0.214*	-0.190*	-0.123*	-0.156*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
NGTA	0.051*	0.048*	0.031*	0.040*	0.031*	0.022*	0.041*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tenure	0.819*	0.845*	0.866*	0.824*	0.745*	0.472*	0.246*
	(0.06)	(0.10)	(0.08)	(0.08)	(0.06)	(0.06)	(0.09)
Profit	0.776*	0.719*	0.524*	0.543*	0.449*	0.332*	0.232**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Collateral Ratio	-0.037	-0.039	-0.198**	-0.035	0.102	0.132***	0.192**
	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)	(0.08)	(0.09)
Shield	-1.837	-0.082	-2.021	-1.085	-3.424*	0.190	-0.646
	(2.01)	(1.40)	(1.42)	(1.54)	(1.06)	(1.22)	(1.00)
R-square	0.7039						

Note: single, double and triple asterisks (*) denote significance at 1%, 5% and 10% confidence level respectively

Table 8 Results of the SUR model in Measuring A Farm's Ability to Meet its Expected Debt over the Next 12 Months

Variable \ Group	Group1	Group2	Group3	Group4	Group5	Group6	Group7
Log (lag of assets to expected debt ratio)	-0.161*	0.039	0.297**	0.232**	0.338*	0.790*	0.643**
	0.02	0.01	0.01	0.01	0.01	0.01	0.01
NROA	-0.029**	-0.063*	-0.018	-0.048*	-0.017	-0.032	-0.036*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.185*	-0.112*	-0.116*	-0.142*	-0.155*	-0.053*	-0.103*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
NGTA	0.020*	0.027*	0.016*	0.011**	0.009***	0.013*	0.019*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)	(0.01)
Tenure	0.479*	0.705*	0.655*	0.733*	0.699*	0.592*	0.435*
	(0.07)	(0.08)	(0.07)	(0.08)	(0.06)	(0.06)	(0.09)
Collateral Ratio	0.468*	0.314*	0.213*	0.092	0.575*	0.222*	0.428*
	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)
Shield	-2.424*	-2.62*	-2.791*	-2.698*	-1.831*	-1.924*	-1.869*
	(0.27)	(0.26)	(0.28)	(0.25)	(0.23)	(0.25)	(0.26)
WC/VFP	0.300*	0.172*	0.308*	0.266*	0.268*	0.230*	0.272*
	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
VFP/Debt	0.699*	0.698*	0.517*	0.543*	0.443*	0.328*	0.310*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
NETINC/VFP	0.391*	0.548*	0.324*	0.666*	0.262*	0.461*	0.502*
	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.07)	(0.09)
R-square	0.7629						

Note: single, double and triple asterisks (*) denote significance at 1%, 5% and 10% confidence level respectively

Table 9 Asset Correlation Matrix By the SUR Model

Risk Rating	1	2	3	4	5	6	7
1	1	0.289	0.306	0.222	0.235	0.180	0.238
2		1	0.200	0.152	0.243	0.151	0.189
3			1	0.222	0.225	0.165	0.220
4				1	0.181	0.162	0.102
5					1	0.127	0.093
6						1	0.128
7							1

Table 10 Predicted Probability of Default (PD) by the SUR Model and Simulation

Risk Rating	Threshold 1		Threshold 2		Average Debt
	PD (%)	Std. of Default (%)	PD (%)	Std. of Default (%)	
1	0.01	1.00			163,492
2	0.042	2.05	0.012	1.10	218,952
3	0.092	3.03	0.012	1.10	291,167
4	0.252	5.01	0.1	3.16	357,812
5	0.816	9.00	0.35	5.91	378,965
6	0.894	9.41	0.512	7.14	415,831
7	2.612	15.95	2.278	14.92	481,544
Weighted Average	0.895		0.643		

Table 11 Default Correlation by the SUR model and Simulation

Risk Rating	Threshold 1							Threshold 2						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	1							1						
2		1				0.020	0.009		1				0.025	
3			1	0.012	0.005	0.004	0.028			1				0.035
4				1	0.013	0.042	0.024				1		0.051	0.012
5					1	0.029	0.026					1	0.015	0.023
6						1	0.030						1	0.028
7							1							1

Table 12 Distribution of Asset Correlation Coefficients by Copulas

Copula	Mean	Standard Deviation	Quantiles			
			5th	25th	50th	75th
Gaussian	0.108	0.091	-0.027	0.042	0.101	0.167
Student's t	0.110	0.083	-0.020	0.051	0.105	0.166

Table 13 Estimated Asset Correlation Matrix by Copulas

Risk Rating	Gaussian Copula							t Copula						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	1	0.114	0.106	0.116	0.112	0.113	0.108	1	0.110	0.105	0.117	0.117	0.113	0.114
2		1	0.097	0.107	0.110	0.107	0.097		1	0.102	0.110	0.108	0.103	0.106
3			1	0.089	0.105	0.112	0.099			1	0.103	0.112	0.105	0.101
4				1	0.107	0.118	0.110				1	0.109	0.107	0.110
5					1	0.121	0.107					1	0.116	0.107
6						1	0.110						1	0.113
7							1							1

Table 14 Predicted Probability of Default (PD) by Copulas

Risk Rating	Gaussian Copula				t Copula				Average Debt
	Threshold 1		Threshold 2		Threshold 1		Threshold 2		
	PD (%)	Std. of Default (%)	PD (%)	Std. of Default (%)	PD (%)	Std. of Default (%)	PD (%)	Std. of Default (%)	
1	0.022	1.48	0.008	0.89	0.004	0.63			163,492
2	0.050	2.24	0.012	1.10	0.036	1.90	0.002	0.45	218,952
3	0.134	3.66	0.010	1.00	0.058	2.41	0.002	0.45	291,167
4	0.250	4.99	0.094	3.06	0.094	3.06	0.034	1.84	357,812
5	0.558	7.45	0.230	4.79	0.258	5.07	0.084	2.90	378,965
6	0.800	8.91	0.448	6.68	0.408	6.37	0.202	4.49	415,831
7	2.070	14.24	1.758	13.14	1.258	11.15	1.076	10.32	481,544
Weighted Average	0.73		0.50		0.40		0.28		

Table 15 Default Correlation by Copulas

Risk Rating	Gaussian Copula													
	Threshold 1							Threshold 2						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	1						0.007	1						
2		1				0.018			1				0.027	
3			1	0.009		0.009	0.010			1				
4				1	0.002	0.031	0.010				1		0.008	0.011
5					1	0.011	0.008					1		0.013
6						1	0.018						1	0.001
7							1							1
	t Copula													
1	1					0.049	0.028	1						
2		1	0.087	0.034	0.020	0.048	0.055		1				0.099	0.043
3			1	0.053	0.064	0.038	0.042			1			0.099	
4				1	0.037	0.070	0.049				1	0.037	0.096	0.051
5					1	0.071	0.061					1	0.076	0.057
6						1	0.074						1	0.069
7							1							1

Table 16 Expected Loss (EL) and Unexpected Loss (UL)

Type	Expected Loss (%)			Unexpected Loss (%)		
	SUR Model	Gaussian Copula	t Copula	SUR Model	Gaussian Copula	t Copula
Threshold 1	0.218	0.175	0.098	1.051	0.930	0.734
Threshold 2	0.161	0.126	0.071	0.912	0.793	0.625
Average	0.190	0.151	0.085	0.982	0.862	0.680

Table 17 Comparison of the Estimated Asset Correlation and Default Correaltin by Gaussian Copula and the SUR Model

Risk Rating	Asset Correlation													
	Gaussian Copula							SUR Model						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	1	0.114	0.106	0.116	0.112	0.113	0.108	1	0.289	0.306	0.222	0.235	0.180	0.238
2		1	0.097	0.107	0.110	0.107	0.097		1	0.200	0.152	0.243	0.151	0.189
3			1	0.089	0.105	0.112	0.099			1	0.222	0.225	0.165	0.220
4				1	0.107	0.118	0.110				1	0.181	0.162	0.102
5					1	0.121	0.107					1	0.127	0.093
6						1	0.110						1	0.128
7							1							1

Default Correlation

Risk Rating	Gaussian Copula							SUR Model						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	1						0.007	1						
2		1				0.018			1				0.020	0.009
3			1	0.009		0.009	0.010			1	0.012	0.005	0.004	0.028
4				1	0.002	0.031	0.010				1	0.013	0.042	0.024
5					1	0.011	0.008					1	0.029	0.026
6						1	0.018						1	0.030
7							1							1

CURRICULUM VITAE

Yan Yan

Department of Agricultural and Consumer Economics, UIUC
1301 West Gregory Drive, Urbana, IL 61801-3605
Email: yan.y.2009@gmail.com Phone: 952-457-5994 (mobile)

Education

- PhD, Agriculture Finance, University of Illinois at Urbana-Champaign, 2009
  Dissertation: Empirical Analysis of Farm Credit Risk under the Structure Model
  Committee: Peter Barry, Nicholas Paulson (Chair), James Gentry, Gary Schnitkey, Hayri Önal/
- MS, Finance, University of Illinois at Urbana-Champaign, 2006
- MA, Economics, Southwestern University of Finance and Economics, China, 1993
- BA, Agricultural Economics, Southwestern University of Finance and Economics, China, 1990

Research Interests

- Agricultural and consumer finance
- Risk management
- Financial planning
- Decision making under uncertainty
- Agricultural policy

Professional Experience

- Credit Risk and Policy Analyst, Card and Retail Services, HSBC, December 2006-Present
- Teaching Assistant, Banking and Management, International Studies and Programs, University of Illinois at Urbana-Champaign, July 2006-November 2006
- Research Associate, Center for Farm and Rural Business Finance, University of Illinois at Urbana-Champaign, August 2002-May 2006
- Manager, CIM, Sichuan Branch Banking Business Department, Agricultural Bank of China, July 1997-July 2001
- Credit Risk and Policy Analyst, CIM, Sichuan Branch Banking Business Department, Agricultural Bank of China, February 1993-June 1997

Honors

- Colvin Fellowship, University of Illinois at Urbana-Champaign, 2003-2005
- Research Assistantship, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, 2005-2006, 2002-2003
- Excellent Unit in Banking Statistics of the Year, the People's Bank of China (the central bank in China), January 1997, 1998, 1999, 2000 and 2001

- Excellent Development Program of Statistical Analyzing System (co-developer), Agricultural Bank of China, September 1998
- Outstanding Employee of the Year, Agricultural Bank of China, June 1995
- Excellent Student Fellowship, Southwestern University of Finance and Economics, 1987- 1990

Publications

- Yan Y. and P. Barry, Loss-Given-Default on Farm Real Estate Loan: Probability of Full Recovery, Agricultural Finance Review, Volume 66, Issue 1, 2006, pp 47 – 59
- Yan Y. and X. Shi, Empirical Analysis of Loan Portfolio Risk and Performance under CAPM and Its Implication to Loan Portfolio Management, Sichuan Finance, Jan.1999, pp. 41-44. Reprinted in Finance and Insurance, China Remin University, May 1999, pp. 144-147

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- Measurement of Farm Credit Risk: SUR Model and Simulation Approach, with P. Barry, N. Nicholas and G. Schnitkey, selected paper presented at AAEA Annual Meeting, Milwaukee, Wisconsin, 2009
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- Exploring the Possible Principal-Agent Problem in Farm Operation, 2005